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Discrimination and allostatic load in black middle-aged and older adults: A systematic review and meta-analysis

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ABSTRACT

Background: Perceived discrimination has been associated with elevated allostatic load (AL), but findings among Black middle-aged and older adults are inconsistent. A focused synthesis is lacking, limiting understanding of how discrimination becomes biologically embedded. This systematic review and meta-analysis aim to clarify the discrimination and AL relationship in Black individuals during aging and highlight key methodological and contextual factors.

Methods: A systematic search of seven databases following PRISMA guidelines included studies on discrimination and AL in Black adults aged 40 and older. AL measures were multisystem indexes of stress-related biomarkers. Study quality was assessed using ROBINS-E, and a random-effects meta-analysis estimated the overall effect size.

Results: Five studies met the inclusion criteria. Four reported significant associations between discrimination, particularly everyday or adolescent exposure, and higher AL. One study found a negative association moderated by coping mechanisms, while another revealed a significant interaction with hopefulness. Meta-analysis of four studies showed a small, non-significant pooled effect (Hedges's $g = 0.132$; 95 % CI: −0.338–0.602; $p = 0.582$) with high heterogeneity ($I^2 = 94.24$ %). Stronger associations appeared in studies using broader biomarker panels and more recent discrimination measures.

Conclusions: This study highlights an inconsistent and heterogeneous relationship between discrimination and AL in Black middle-aged and older adults. While evidence suggests a general link, findings remain mixed due to methodological variability. The meta-analysis found no significant pooled effect, reflecting limited and diverse studies. Future research should prioritize longitudinal designs, standardized measures, and consideration of coping and resilience factors.

1. Introduction

Discrimination is a widespread and deeply rooted psychosocial stressor and social determinant of health that disproportionately affects Black individuals, including those in midlife and older adulthood (Moody and Lewis, 2023; Williams, 2018). Defined as differential treatment based on one's identity, outward characteristics, or group membership, discrimination represents a significant psychosocial stressor involving unfair treatment and experiences of personal rejection (Lewis et al., 2006; Williams et al., 2003). Common examples include

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being treated with less courtesy or respect, receiving poorer service, being perceived as less intelligent or dishonest, or facing threats and harassment. These experiences may reflect general discrimination (unfair treatment without specified attribution) or attribution-specific discrimination, such as racial, gender-based, or age-related bias. Approximately 92 % of Black American adults report experiencing discrimination across domains such as employment, healthcare, education, and interpersonal relationships, with these experiences accumulating over the lifespan (Bleich et al., 2019). This chronic exposure is strongly associated with elevated risks of hypertension, diabetes, cardiovascular disease, and premature mortality (Agbonlahor et al., 2024; Lawrence et al., 2023; Reid and Earnshaw, 2023; Williams et al., 2019b) through mechanisms that remain under investigation.

Lifetime exposure to discrimination can disrupt both physical and mental health through biological stress mechanisms (Berger and Sarnyai, 2015). Midlife and older adulthood are particularly critical for examining these effects, as physiological dysregulations, often incubated during adulthood, tend to intensify with age (Lupien et al., 2009). Midlife thus represents an incubation period in which chronic exposure to psychosocial stressors, such as discrimination accelerates biological aging, whereas later life reflects the manifestation phase, when these effects emerge as chronic disease and cognitive decline. This period constitutes a window of vulnerability (Lupien et al., 2009), during which stress-related wear and tear *might be* biologically embedded and increasingly consequential for health.

A key biological pathway linking discrimination to adverse health outcomes might be explained by allostatic load (AL), the cumulative physiological 'wear and tear' of chronic stress exposure on systems such as the hypothalamic-pituitary-adrenal (HPA) axis and the sympathetic-adrenal-medullary (SAM) system (Cohen et al., 2016; McEwen and Akil, 2020). Chronic exposure to psychosocial stressors like discrimination can lead to dysfunction across multiple biological systems, including neuroendocrine, immune, metabolic, and cardiovascular systems, through mitochondrial dysfunction, oxidative stress, and inflammation (Epel et al., 2018; Picard et al., 2014). Elevated AL has been linked to biological aging and an increased risk of chronic disease, particularly in older populations (Epel, 2020; Polick et al., 2024). Notably, prior research has shown that Black older adults exhibit higher levels of AL compared to their White counterparts (Bell and Ferraro, 2025), reflecting cumulative physiological costs of chronic social adversity.

Black adults in the United States face disproportionate exposure to both structural and interpersonal discrimination across the life course, rooted in a legacy of structural racism, residential segregation, and economic and healthcare inequities (Bailey et al., 2017; Williams et al., 2019a). Structural racism has systematically constrained access to education, wealth accumulation, neighborhood resources, and quality healthcare, producing sustained psychosocial and physiological stressors that accumulate across generations. These exposures compound over decades, resulting in chronic activation of stress-response systems and greater biological vulnerability during midlife and later life (Lupien et al., 2009; McEwen and Akil, 2020).

Although prior reviews have examined the relationship between discrimination and AL across racially diverse populations (Miller et al., 2021). Most existing studies did not isolate findings for Black adults or focus specifically on aging and employed generic instruments to assess perceived discrimination, such as the EDS (Williams et al., 1997), which capture unfair treatment broadly but do not always specify racial attribution. Consequently, evidence remains inconsistent: some studies; Ong et al. (2017) and Van Dyke et al. (2020) found positive relationships between general perceived discrimination and higher AL. In contrast, Mitchell et al. (2020) reported a negative relationship using a general perceived discrimination measure, while studies examining attribution-specific discrimination, such as racial discrimination (Allen et al., 2019; Thomas Tobin et al., 2022), also yielded divergent associations with AL. These inconsistencies indicate that the observed direction of the discrimination–AL relationship may depend on how discrimination is conceptualized—whether as broad perceived unfair treatment or as experiences tied to specific attributions such as race. The Miller et al. (2021) review similarly noted a general positive link but attributed inconsistencies to methodological variation in AL scoring and biomarker selection. These gaps highlight the need for a population-specific synthesis focused on Black midlife and older adults, among whom both discrimination exposure and physiological vulnerability are most pronounced. We aimed to address these gaps by (a) focusing exclusively on Black adults aged $\geq$ 40 years, (b) conducting a quantitative synthesis where possible, and (c) systematically evaluating how methodological variability between studies might influence results.

This systematic review and meta-analysis address this gap by synthesizing existing evidence on the relationship between perceived discrimination (general and attribution-specific forms) and AL in Black middle-aged and older adults. By focusing on this understudied population and applying rigorous methodology, this review seeks to clarify the physiological connection to discrimination and contribute to a deeper understanding of how cumulative psychosocial stress drives health disparities across the aging trajectory. We hypothesize that greater exposure to perceived discrimination—whether general or attribution-specific—is associated with higher AL, reflecting greater multisystem physiological dysregulation, among Black middle-aged and older adults.

2. Methods

This systematic review and meta-analysis followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Liberati et al., 2009), and the Meta-analysis of Observational Studies in Epidemiology (MOOSE) guidelines and criteria (Stroup et al., 2000). The research question based on the Participant, Exposure of Interest, and Outcome (PEO) was stated as: 'Is AL a biological measure of discrimination (general or attribute-specific) among Black middle-aged and older adults? A three-phase search strategy was developed in collaboration with a health sciences librarian to ensure methodological rigor. The search strategy was developed iteratively with a health sciences librarian at the Hardin Library for the Health Sciences. We piloted the search in PubMed, screened results to confirm that key terms and relevant studies were captured, and refined the strategy before applying it across the remaining databases and targeted journals. Final tailored strategies for each database, including controlled vocabulary and keywords, are detailed in Appendix A, Table A.1.

2.1. Inclusion and exclusion criteria for selecting studies

The PEO framework was used to define the inclusion and exclusion criteria, guiding the selection of studies, data extraction, and synthesis of findings. In addition, the types of studies considered, such as study designs, were a factor in determining study eligibility.

2.1.1. Participants (P)

Studies were included if they involved middle-aged and older adult participants who self-identified as Black or African American, ensuring that racial identity was a central focus of the analysis. Specifically, studies were considered if they included participants aged 40 years and older, or if the sample's mean age was $\geq$ 50 years with a standard deviation of 10 or higher, indicating that the majority of participants were within the target age range. This approach ensured conceptual consistency with our focus on midlife and older adulthood, while preserving relevant studies. Moreover, studies that included multiple racial groups were considered only if they provided stratified results for Black participants.

2.1.2. Exposure of interest (E)

The primary exposure of interest was perceived discrimination,

encompassing both general and attribution-specific forms (e.g., racial, gender, age-related) of unfair treatment experienced across life domains, including social, workplace, healthcare, and other significant contexts. We included studies that assessed both everyday and lifetime discrimination, provided they used validated scales or self-report instruments, such as the Everyday Discrimination Scale (Williams et al., 1997), to capture experiences of rejection and unfair treatment, which are central to the construct of discrimination

2.1.3. Outcomes (O)

AL was the central outcome of this systematic review. We included studies that assessed AL using a cumulative index, composite score, or weighted factor score, incorporating biomarkers from multiple physiological systems. These systems included cardiovascular function (e.g., blood pressure, heart rate variability), metabolic regulation (e.g., lipid profiles, glucose, insulin), inflammatory activity (e.g., pro- and anti-inflammatory cytokines), and neuroendocrine function (e.g., cortisol, dehydroepiandrosterone sulfate [DHEA-S]). Studies that assessed biomarkers from a single system, such as cortisol for neuroendocrine function or blood pressure for cardiovascular health, without incorporating markers from additional systems, were excluded, as they may reflect isolated allostatic states rather than the multisystemic dysregulation central to the construct of AL.

2.1.4. Type of studies

Eligible study designs included observational studies, such as prospective and retrospective cohorts, cross-sectional, and case-control studies. Experimental and quasi-experimental studies were also considered if they met the inclusion criteria and provided relevant data on the relationship between discrimination and AL. Interventional studies were included only if they reported outcomes related to both discrimination and AL. Exclusions based on study type included editorials, letters, and commentaries. Review articles and systematic reviews were also excluded, ensuring the inclusion of only primary research studies. Non-academic sources were excluded by applying limits to ensure only peer-reviewed academic journal articles and dissertations were included. To maintain methodological comparability, we also excluded studies that (a)) reported duplicate findings from the same cohort when the included publication provided more comprehensive and extractable data necessary for quantitative synthesis (e.g., regression coefficients, standard errors, and sample sizes), (b) modeled discrimination only as a moderator or interaction term rather than a primary exposure, or (c) did not provide extractable quantitative estimates suitable for synthesis. These decisions ensured conceptual alignment with our primary research question and adherence to the inclusion criteria.

2.2. Three-phase search strategy

Search strategies were developed in collaboration with a health sciences librarian experienced in systematic reviews (JD). A three-phase approach was used: (1) keyword development, (2) database searching, and (3) manual reference screening. An initial exploratory search across PubMed, CINAHL, Embase, Cochrane CENTRAL, PsycINFO, Scopus, and AgeLine helped identify relevant text words and index terms. These were refined to improve search specificity and sensitivity. In the second phase, a systematic search was conducted across the same databases using tailored strategies that combined MeSH terms, controlled vocabulary, and text word variations with Boolean operators ('OR' and 'AND') to ensure comprehensive coverage (Appendix A, Table A.1). The third phase involved manually screening the reference lists of included studies to identify additional eligible articles not captured in the database search. All database searches were conducted and overseen by the expert librarian (JD) to ensure methodological rigor.

2.3. Selection process

All retrieved records were first imported into EndNote to remove duplicates. Two reviewers (AH, PA) independently screened titles and abstracts based on the inclusion criteria, followed by full-text reviews of potentially eligible studies. Discrepancies were resolved through discussion, with a third reviewer (JNST) consulted to arbitrate any disagreements. In instances where multiple publications reported findings from the same cohort, we included the study that provided the most comprehensive data on discrimination and AL, prioritizing the largest analytic sample, or included important covariates, and most detailed reporting of effect estimates. Duplicate reports or secondary analyses from the same cohort were excluded to avoid double-counting participants.

2.4. Data items and extraction

Data on study characteristics (e.g., author, year, design, country) and participant demographics (e.g., sample size, mean age, race, and sex) were extracted. Methodological details were also recorded, including measures of discrimination, categorized as either general perceived discrimination (unattributed unfair treatment) or attribution-specific discrimination (e.g., racial, gender, or age-based), as well as by time frame (e.g., everyday or lifetime). For each study, we extracted estimates of the association between discrimination and AL, along with the AL biomarkers, corresponding physiological systems, and scoring methods used (e.g., population-based thresholds, clinical cutoffs). Data extraction was conducted independently by two reviewers (AH, PA) and cross-checked for accuracy. Any discrepancies were resolved through discussion or, when necessary, consultation with a third reviewer (JNST).

2.5. Quality assessment

We assessed the methodological quality of included studies using the Risk of Bias in Non-randomized Studies of Exposure (ROBINS-E) tool (Higgins et al., 2024). This tool evaluates seven key domains of bias: confounding, measurement of the exposure (discrimination), selection of participants, post-exposure interventions, missing data, measurement of outcomes (AL index), and selection of reported results. Each domain was assessed using structured signaling questions, resulting in three judgments per study: the overall risk of bias (low, moderate, serious, or critical), the predicted direction of bias, and whether the bias level could compromise conclusions about the exposure-outcome relationship. An overall risk of bias rating was assigned based on the highest level of bias observed across domains. Studies were categorized as follows: low risk (bias well-addressed), moderate risk (minor concerns unlikely to affect conclusions), serious risk (major concerns that may impact validity), and critical risk (substantial bias rendering findings unreliable). Studies rated as having a critical risk of bias were excluded from the final synthesis. Two independent reviewers (AH, PA) evaluated each study across all domains, with a third reviewer verifying assessments for consistency (JNST). Discrepancies were resolved through consensus discussions. Final ROBINS-E judgments by domain are presented in Table 2.

2.6. Data synthesis and meta-analysis

We conducted a narrative synthesis to summarize the findings, contextualizing them in relation to methodological variations such as population characteristics, study design, type of perceived discrimination (e.g., lifetime vs. everyday), and the specific components of the AL index measured. To visually characterize the AL index across studies, we used a heatmap to display the number and types of biomarkers included, along with the biological systems they represented. A meta-analysis was also performed to quantitatively synthesize the results. For each study, we extracted Pearson correlation coefficients (r) representing the linear

association between perceived discrimination and the AL index. When only standardized regression coefficients were reported, they were converted to r using Comprehensive Meta-Analysis (CMA) software, Version 4 (Borenstein et al., 2022). Statistical heterogeneity was assessed using the I^2 statistic. In cases of substantial heterogeneity, a random-effects model was applied to account for between-study variability and to yield a more generalizable estimate of the overall effect size. Forest plots were generated to display individual and pooled effect sizes. For continuous outcomes, Hedges' g was calculated to adjust for differences in sample sizes across studies. All effect sizes were reported with corresponding 95 % confidence intervals (CIs). Publication bias was evaluated using funnel plots and Egger's test for asymmetry. All statistical analyses were conducted using CMA software, Version 4.

3. Results

3.1. Study characteristics

Using predefined search terms, we identified a total of 5043 records across five databases: PubMed, CINAHL, PsycINFO, ProQuest Dissertations, and Scopus. After removing 646 duplicate or ineligible records, 4397 articles remained for title and abstract screening. The most common reasons for full-text exclusion included the absence of a discrimination measure, lack of reported AL scores, studies involving racially mixed populations without stratified analyses for Black participants, and duplicate data (more than one study reporting findings on the same study population/sample). A total of five studies met the inclusion criteria for this systematic review (Fig. 1), encompassing a combined sample of 1961 Black middle-aged and older adults. All studies were conducted in the United States. Participant mean ages ranged from 41.7 to 66 years, and the proportion of female participants varied between 55.9 % and 100 % across studies. The included studies employed both cross-sectional and longitudinal designs (Table 1). Specifically, four studies were cross-sectional (Allen et al., 2019; Thomas Tobin et al., 2022; Van Dyke et al., 2020), while one study used a longitudinal design (Mitchell et al., 2020). The study selection process and reasons for exclusion are detailed in the PRISMA flowchart (Fig. 1)

3.2. Discrimination measures across studies

Across the five included studies, discrimination was assessed using validated self-report instruments that varied in attribution (general vs. race-specific), life-course timing (everyday vs. lifetime), and scoring methodology. Some studies measured unfair treatment with race as one of several possible attributions, while others focused explicitly on racial discrimination. The psychometric properties and operationalization of each instrument are described below.

Allen et al. (2019) used the Experiences of Discrimination (EOD) Scale developed by Krieger et al. (2005), which captures racial/ethnic discrimination across nine domains, including education, employment, housing, and medical care. Participants reported whether they had "ever experienced discrimination, been prevented from doing something, or been hassled or made to feel inferior" due to race, ethnicity, or color. This measure therefore assessed attribution-specific (racial) discrimination, capturing lifetime exposure to racially motivated unfair treatment.

Ong et al. (2017) employed two instruments. The EDS, also referred to as the Everyday Unfair Treatment Scale (Williams et al., 1997), includes nine items assessing routine mistreatment, such as being treated with less respect. A follow-up attribution question asked participants to identify the perceived reasons for these experiences, including whether their perceptions were due to race. The second instrument, the Lifetime

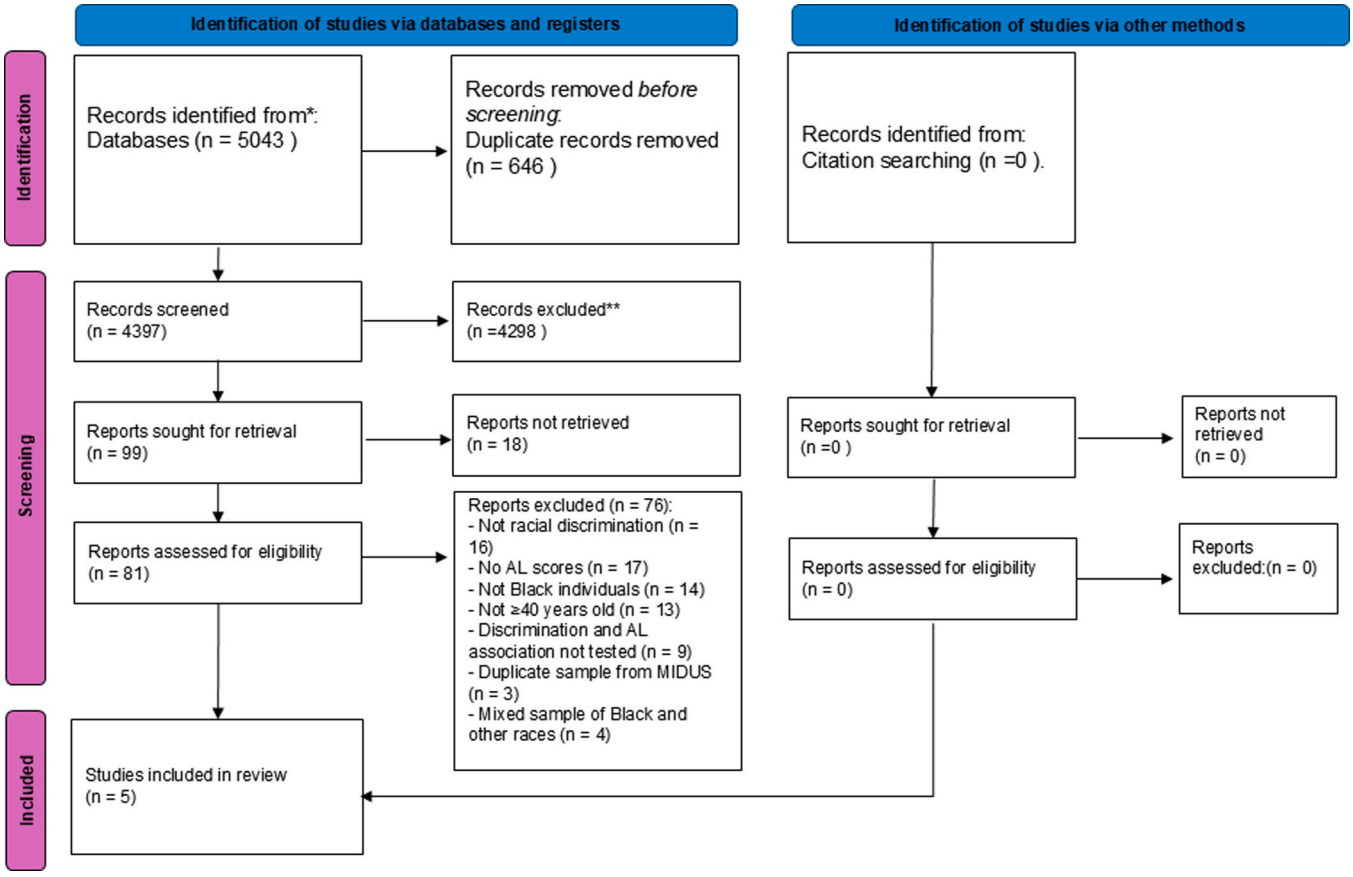


Fig. 1. PRISMA flow diagram of study selection process. This diagram outlines the number of records identified, screened, excluded, and included at each stage of the systematic review following PRISMA guidelines.

Table 1
Characteristics and primary findings of studies examining discrimination and allostatic load.

Author (year)	Study Design	Sampling Region/N	Black % and/ or n	Age Mean (±SD)	♀ %	Discrimination Measure	Measure Attribution/ Timeframe of Discrimination Measurement	Covariates	Discrimination and AL index association
Allen et al. (2019)	Cross-sectional	San Francisco Bay Area, California /207	100	41.7 (5.9)	100	Experiences of Discrimination scale	Racial/Lifetime	Age, Educational Attainment, Poverty Status, Employment Marital Status Health Insurance Neuroticism Medication Use.	**Linear model** Higher discrimination, lower AL (β=−.21; $p < .001$) **Quadratic Model** Discrimination × Strength: (β =.29, p = .01) Discrimination × Emotion: (β =.24, p = .03) Discrimination × Succeed: (β = −.30, p = .01) Discrimination × Help: (β = −.23, p = .02)
Ong et al. (2017)	Cross-sectional	Milwaukee County, Wisconsin/ 233	100	53.6 (10.4)	67.4	Everyday unfair treatment and Lifetime unfair treatment	General/Everyday and lifetime	Age, gender, education, medications, smoke, alcohol, depression, perceived stress	Higher everyday unfair treatment, higher AL (β =.019, 95 % CI [0.001, 0.038]) Lifetime unfair treatment not significant (β =.018, 95 % CI [−0.016, 0.053])
Mitchell et al. (2020)	Longitudinal	National U.S. sample (Health and Retirement Study)/ 8486	12.2 (1039 Black)	66.0 (0.44)[a]	63.9[a]	Lifetime Discrimination scale	General/lifetime	Age, sex, nativity, education, depressive symptoms.	No significant relationship (β = −.019, p > .05) Hopefulness x Discrimination (β =.362; p < 0.01)
Van Dyke et al. (2020)	Cross-sectional	National sample (MIDUS II)/ 1204	18.8 (226 Black)	50.9 (10.6)[a]	67.7[a]	Composite score (everyday, lifetime, Workplace Discrimination)	General/Lifetime combined with everyday	Age, sex, marital status, employment, SES, medications, health behaviors, neuroticism and negative affect	Higher discrimination, increased AL (β =.44, p = .004)
Thomas Tobin et al. (2022),	Cross-sectional	Davidson County, Tennessee/ 260	100	56.3 (6.7)	55.9	Early life Racial Discrimination	Racial Adolescence	Age, SES, education, smoking, alcohol, physical activity	Higher ELRD adolescence, higher AL (IRR = 1.32, $p < 0.05$). ELRD childhood (IRR = 0.88, 95 % CI [0.62–1.24]), and adulthood (IRR = 1.16, 95 % CI [0.98–1.37]) no association with AL

[a] Black participants' data; W = White; B = Black; A = Asian; H = Hispanic; O = other, β = standardized coefficient; IRR = incidence risk ratio; CI = confidence interval.

Unfair Treatment Scale (Kessler et al., 1999), includes 11 dichotomous items capturing major discriminatory events, such as being denied housing or a loan. Respondents indicated whether these events were due to race or other characteristics. Thus, this study measured general perceived discrimination across both everyday and lifetime contexts.

Mitchell et al. (2020) utilized the *Lifetime Discrimination Scale* (Kessler et al., 1999), which evaluates significant lifetime discriminatory events (e.g., unfair treatment by police, in healthcare, or in housing) across 11 domains. While respondents could identify the perceived reasons for these experiences, the study analyzed the total discrimination score, reflecting general perceived discrimination rather than attribution-specific (e.g., racial) discrimination. Accordingly, this measure captures general lifetime discrimination exposure.

Van Dyke et al. (2020) developed a Pervasive Discrimination Score by combining three validated measures: the EDS (Williams et al., 1997), the LTD (Kessler et al., 1999), and the Workplace Discrimination Scale (Sternthal et al., 2011), This composite reflected the number of domains—everyday, lifetime, and workplace—in which participants reported discrimination levels above the race-specific median. Although racial discrimination was among the attributions assessed, the study treated the combined score as a measure of general perceived discrimination, integrating exposure across multiple contexts over the life course.

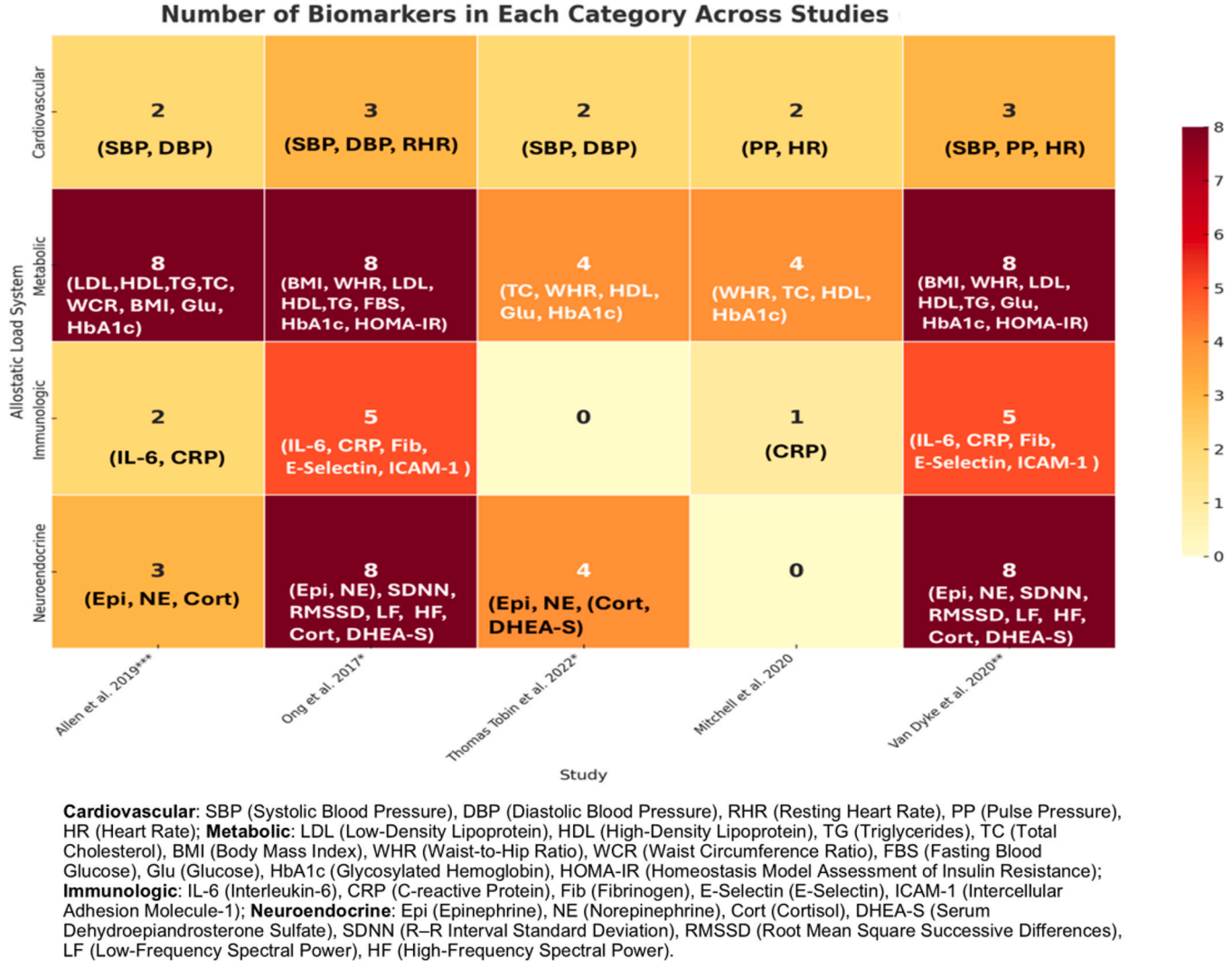
Thomas Tobin et al. (2022) assessed racial discrimination using the Early Life Racial Discrimination (ELRD) Measure. Participants were asked whether they had experienced a racially discriminatory event that

"bothered them a great deal" and to report the age at which the most significant incident occurred. Responses were categorized into life stages: childhood (0–12 years), adolescence (13–18 years), and adulthood (19 + years). This measure thus assessed attribution-specific (racial) discrimination, with a focus on developmental timing during early life.

3.3. Allostatic load assessment across studies measurement

The studies assessed AL using a comprehensive set of biomarkers representing four primary physiological systems: neuroendocrine, immunologic, metabolic, and cardiovascular (Fig. 2). Across studies, AL indices spanned 8–24 biomarkers covering 3–7 physiological systems. Two studies used system-based scoring (Ong et al., 2017; Van Dyke et al., 2020), and three used biomarker-count scoring (Allen et al., 2019; Mitchell et al., 2020; Thomas Tobin et al., 2022). For synthesis and meta-analysis, we used the total multisystem AL index from each study; subsystem scores (e.g., immune-only, metabolic-only) were not combined or analyzed as separate effects. Neuroendocrine markers included indicators of autonomic nervous system (ANS) activity, specifically epinephrine (Epi), norepinephrine (NE), and heart rate variability (HRV), as well as hormones of the HPA axis, namely cortisol and dehydroepiandrosterone sulfate (DHEA-S). Immunologic function was evaluated using C-reactive protein (CRP) and interleukin-6 (IL-6). Metabolic markers included glucose, glycated hemoglobin (HbA1c), and body mass index (BMI), while cardiovascular function was assessed through systolic (SBP) and diastolic blood pressure (DBP) (Fig. 2). Some studies incorporated biomarkers from all four systems to compute a comprehensive AL index, as seen in (Allen et al., 2019), Ong et al. (2017), and Van Dyke et al. (2020). However, other studies excluded certain systems, such as the neuroendocrine system in Mitchell et al. (2020) or the immunologic system in Thomas Tobin et al. (2022) (see Fig. 2). Despite these differences, certain biomarkers were consistently used across studies. Cortisol and epinephrine/norepinephrine were included in all studies that assessed the neuroendocrine system. CRP was universally used in studies evaluating the immunologic system, HbA1c was consistently used for the metabolic system, and SBP was the most commonly included cardiovascular marker (Fig. 2). Only two studies, Ong et al. (2017) and Van Dyke et al. (2020), evaluated HRV-based measures to assess autonomic cardiac regulation. These included time-domain metrics such as the standard deviation of normal-to-normal R-R intervals (SDNN) and the root mean square of successive differences (RMSSD), as well as frequency-domain components like low-frequency (LF) and high-frequency (HF) power (see Fig. 2).

Regarding scoring methodologies, two primary approaches were used to calculate AL scores: the physiological system-based approach and the biomarker-based approach. The system-based approach, employed by Ong et al. (2017) and Van Dyke et al. (2020), grouped



Cardiovascular: SBP (Systolic Blood Pressure), DBP (Diastolic Blood Pressure), RHR (Resting Heart Rate), PP (Pulse Pressure), HR (Heart Rate); **Metabolic**: LDL (Low-Density Lipoprotein), HDL (High-Density Lipoprotein), TG (Triglycerides), TC (Total Cholesterol), BMI (Body Mass Index), WHR (Waist-to-Hip Ratio), WCR (Waist Circumference Ratio), FBS (Fasting Blood Glucose), Glu (Glucose), HbA1c (Glycosylated Hemoglobin), HOMA-IR (Homeostasis Model Assessment of Insulin Resistance); **Immunologic**: IL-6 (Interleukin-6), CRP (C-reactive Protein), Fib (Fibrinogen), E-Selectin (E-Selectin), ICAM-1 (Intercellular Adhesion Molecule-1); **Neuroendocrine**: Epi (Epinephrine), NE (Norepinephrine), Cort (Cortisol), DHEA-S (Serum Dehydroepiandrosterone Sulfate), SDNN (R–R Interval Standard Deviation), RMSSD (Root Mean Square Successive Differences), LF (Low-Frequency Spectral Power), HF (High-Frequency Spectral Power).

Fig. 2. Heat map summarizing the distribution of AL biomarkers across studies by physiological system (cardiovascular, metabolic, immunologic, and neuroendocrine). Darker shading indicates a greater number and diversity of biomarkers included within each system for a given study.

biomarkers according to their corresponding physiological systems. A system was classified as dysregulated if at least one biomarker within it exceeded a predefined threshold, typically defined by population-based quartiles (i.e., values falling within the highest or lowest 25 % of the distribution). Each system was assigned a binary score (0 = normal, 1 = dysregulated), and the total AL score was calculated as the sum of dysregulated systems, with possible scores ranging from 0 to 7. The systems assessed in this approach included the HPA axis, sympathetic and parasympathetic nervous systems, immunologic function, glucose metabolism, lipid metabolism, and cardiovascular function. In contrast, the biomarker-based approach, used by Allen et al. (2019), Mitchell et al. (2020), and Thomas Tobin et al. (2022), calculated AL as the total number of individual biomarkers that exceeded risk thresholds. This method yielded broader score ranges, such as 0–15 in Allen et al. (2019) and 0–11 in other studies. Unlike the system-based approach, which aggregates dysregulation at the system level, the biomarker-based method emphasizes the individual risk phenotype associated with each biomarker. Thresholds for defining dysregulation varied across studies. Ong et al. (2017) and Van Dyke et al. (2020) relied exclusively on population-based quartiles to determine cut-points. In contrast, Mitchell et al. (2020) and Thomas Tobin et al. (2022) used clinical reference ranges based on established medical guidelines. Allen et al. (2019) adopted a hybrid strategy, combining both population-based and clinical thresholds to enhance sensitivity in detecting physiological dysregulation. In all cases, biomarkers were scored dichotomously (0 = normal, 1 = dysregulated), and the final AL score represented the cumulative number of dysregulated biomarkers (see Table 3).

3.4. Relationship between discrimination and allostatic load

Among the five included studies, four reported significant associations between discrimination (general and attribute-specific) and AL, though the direction and nature of these associations varied. Ong et al. (2017) and Van Dyke et al. (2020) found positive associations, indicating that greater exposure to general perceived discrimination was linked to higher AL. Ong et al. reported that everyday unfair treatment was significantly associated with increased AL (B = 0.019; 95 % CI [0.001, 0.038]), while Van Dyke et al. found that a composite measure of discrimination, including everyday, lifetime, and workplace discrimination, was positively associated with AL (B = 0.44, p = 0.004). Both studies employed comprehensive AL indices, incorporating 24 biomarkers across seven physiological systems. In contrast, Allen et al. (2019) observed a significant inverse association between racial discrimination and AL ($\beta = -0.21$, $p < 0.001$), even after adjusting for sociodemographic factors, health status, and personality traits. However, this relationship was significantly moderated by dimensions of the Superwoman Schema (SWS), a culturally embedded coping framework common among Black women. Using a path analysis model with a quadratic specification of discrimination, Allen et al. (2019) identified significant interaction effects between racial discrimination and four of the five SWS subscales. Specifically, the association between discrimination and AL was amplified among women who reported a stronger obligation to present strength ($\beta = 0.29$, $p = 0.01$) and greater emotion suppression ($\beta = 0.24$, $p = 0.03$). In contrast, among those with high levels of motivation to succeed ($\beta = -0.30$, $p = 0.01$) and obligation to help others ($\beta = -0.23$, $p = 0.02$), associations of discrimination with AL were either attenuated or showed curvilinear patterns. Thomas Tobin et al. (2022) identified an exposure timing-specific effect. General perceived discrimination during adolescence (ages 13–18) was significantly associated with higher AL (IRR = 1.32, $p < 0.05$), whereas discrimination experienced in childhood or adulthood was not significantly related to AL (Thomas Tobin et al., 2022). Mitchell et al. (2020), the only longitudinal study, did not find a direct association between lifetime racial discrimination and AL ($\beta = -0.019$, $p > 0.05$). However, a significant interaction emerged. Among individuals with higher levels of racial discrimination, greater hopefulness was associated with increased AL ($\beta = 0.362$, $p < 0.01$), suggesting an inconsistent and heterogeneous moderating effect potentially linked to coping mechanisms or resilience framing (Mitchell et al., 2020).

Two studies did not report significant main associations between discrimination and AL. Mitchell et al. (2020) assessed general lifetime discrimination using a checklist format and observed a non-significant relationship with AL, whereas Thomas Tobin et al. (2022) examined racial discrimination across developmental stages and found that only adolescent exposure, not childhood or adulthood, was linked to higher AL. Both studies used narrower biomarker panels and lifetime or retrospective discrimination measures, which may partially account for these null findings.

The studies varied in the number of biomarkers and physiological systems used to construct AL indices. Ong et al. (2017) and Van Dyke et al. (2020) used the most comprehensive indices, while Allen, et al. (2019) and Thomas Tobin et al. (2022) used 15 and 10 biomarkers, respectively. Mitchell et al. (2020) used eight biomarkers across four systems. Studies with broader biomarker coverage tended to report more consistent associations between discrimination and AL.

Potential moderating effects of age and sex were also explored. Ong et al. (2017) tested for an age × discrimination interaction but found no significant effect (B = 0.001, 95 % CI [−0.001, 0.002]). Similarly, sex × discrimination interactions were examined by Ong et al. (2017) and Van Dyke et al. (2020), but neither study found statistically significant results. For instance, Ong et al. reported a non-significant interaction (B = 0.001, 95 % CI [−0.037, 0.035]), and although Van Dyke et al. found that being female was associated with higher AL (B = 0.26, SE = 0.17, p = 0.12), the interaction with discrimination was not significant.

To estimate the pooled effect size, a meta-analysis was conducted using four eligible studies (Ong et al., 2017, Allen et al., 2019, Mitchell et al., 2020, and Van Dyke et al., 2020). One study was excluded due to the inability to obtain standardized regression coefficients from the text or directly from the study authors (Thomas Tobin et al., 2022), which are required for calculating comparable effect sizes across studies. Given the high heterogeneity across studies ($Q = 52.04$, $df = 3$, $p < 0.001$; $I^2 = 94.24$ %; $Tau^2 = 0.093$), a random-effects model was used. The model yielded a small, non-significant overall effect size between discrimination and AL (Hedges's g = 0.132; 95 % CI [−0.338, 0.602]; p = 0.582) Fig. 3. The prediction interval (−2.109–2.374) indicated substantial variability in potential true effects across contexts. Egger's test did not detect publication bias (intercept = 3.09, 95 % CI [−23.81, 29.99]; p = 0.670), though the small number of studies limits the power of this test (Appendix A, Figure A.1).

3.5. Quality assessment of included studies

As summarized in Table 2, the overall risk of bias across key methodological domains was low. Most studies demonstrated a low risk in measuring the discrimination exposure, except for Thomas Tobin et al. (2022), which assessed early-life discrimination, introducing some uncertainty due to retrospective reporting and potential recall bias. Participant selection was consistently robust, with all studies rated as low risk in this domain. Minor concerns regarding missing data were noted in Allen et al. (2019) and Van Dyke et al. (2020), primarily due to incomplete reporting. However, the extent of missingness was not sufficient to compromise study quality. Despite comprehensive statistical adjustments, residual confounding remained a concern across all studies, indicating the potential influence of unmeasured variables. Outcome measurement of the AL index and reporting practices were consistently reliable, reflecting strong methodological rigor.

4. Discussion

This systematic review and meta-analysis is the first to synthesize evidence on the relationship between perceived discrimination (General and attribute-specific) and AL, specifically among Black middle-aged

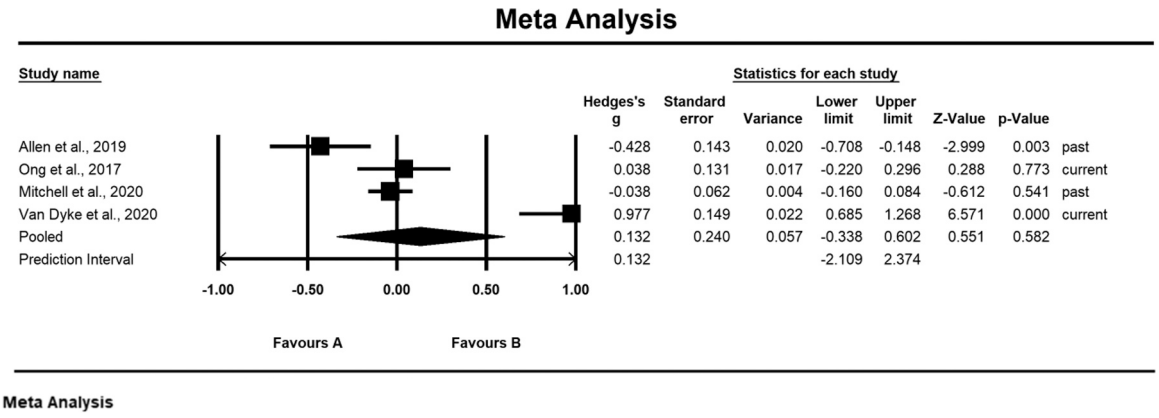


Fig. 3. Forest plot of the association between discrimination and allostatic load. Effect sizes (with confidence intervals) are displayed for each included study, along with pooled estimates from the meta-analysis.

Table 2
Quality evaluation of studies using ROBINS-E by domain of bias.

Study	Confounding	Risk of Bias Domain						
		Measurement of the exposure	Selection of participants into the study	Post-exposure interventions	Missing data	Measurement of outcomes	Selection of reported results	The overall risk of bias
Allen et al. (2019)	Low risk of bias except for concerns of residual confounding	Low risk of bias	Low risk of bias	Low risk of bias	Low risk except for lack of information for which data is missing	Low risk of bias	Low risk of bias	Low risk of bias
Ong et al. (2017)	Low risk of bias except for concerns of residual confounding	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias
Mitchell et al. (2020)	Low risk of bias except for concerns of residual confounding	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias
Van Dyke et al. (2020)	Low risk of bias except for concerns of residual confounding	Low risk of bias	Low risk of bias	Low risk of bias	Low risk except for lack of information for which data is missing	Low risk of bias	Low risk of bias	Low risk of bias
Thomas Tobin et al. (2022),	Low risk of bias except for concerns of residual confounding	Low risk of bias except for the recall bias related to early life discrimination experience	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias	Low risk of bias

and older adults. Across the five included studies, discrimination was generally associated with higher AL, although the direction and magnitude of associations varied considerably. Three studies—Ong et al. (2017), Van Dyke et al. (2020), and Thomas Tobin et al. (2022)—reported positive associations, indicating that greater exposure to discrimination corresponded to higher physiological dysregulation. In contrast, Allen et al. (2019) observed an inverse relationship, and Mitchell et al. (2020) reported a non-significant main effect, though both identified moderating influences such as coping and hopefulness.

A potential explanation for these inconsistencies lies in methodological differences across studies. For example, Ong et al. (2017) and Van Dyke et al. (2020) measured *general perceived discrimination* using the EDS and employed comprehensive AL indices covering multiple stress-responsive systems—neuroendocrine, immune, metabolic, and cardiovascular. These studies reported positive, direct associations between discrimination and AL. In contrast, Allen et al. (2019) and Mitchell et al. (2020) used *lifetime or attribution-specific* discrimination measures—particularly racial discrimination—and narrower biomarker panels that excluded key excluded key neuroendocrine biomarkers such as cortisol. Allen et al. (2019) observed an inverse relationship between racial discrimination and AL, moderated by culturally embedded coping mechanisms (e.g., the Superwoman Schema), while Mitchell et al. (2020), the only longitudinal study, found no significant main association but noted that hopefulness interacted with discrimination in complex ways. Thomas Tobin et al. (2022) further highlighted timing effects, showing that racial discrimination experienced in adolescence, but not childhood or adulthood, predicted higher AL. Collectively, these differences in discrimination type, measurement timeframe, biomarker scope, and analytic specification likely contributed to the heterogeneity and small, non-significant pooled effect observed in the meta-analysis.

Contradictory findings from Allen et al. (2019) and Mitchell et al. (2020) suggest that the relationship between discrimination and AL is neither direct nor linear. Instead, it appears transactional and influenced by moderators such as coping strategies, emotional context, race, and socioeconomic status (Allen et al., 2019; Lazarus and Folkman, 1984). In this review, the term *race* refers to the Black population as a socially constructed group disproportionately exposed to structural and interpersonal discrimination. Because all included participants identified as Black, racial group comparisons were not the focus. However, within-group heterogeneity—such as differences in ethnicity, nativity (U.S.-born versus foreign-born), and cultural background—may influence how discrimination is perceived and physiologically internalized

Table 3
Summary of allostatic load scoring approaches across studies.

Study	Scoring Approach	AL Range	Cut-Point Determination	Standardization Method
(Allen et al., 2019)	Biomarker-Based	0–15	Combined (Population-based + Clinical)	Binary (0 = normal, 1 = dysregulated biomarker)
Ong et al. (2017)	Physiological System-Based	0–7	Population-based quartiles	Binary (0 = normal, 1 = dysregulated system)
Mitchell et al. (2020)	Physiological System-Based	0–7	Clinical thresholds	Binary (0 = normal, 1 = dysregulated system)
Van Dyke et al. (2020)	Physiological System-Based	0–7	Population-based quartiles	Binary (0 = normal, 1 = dysregulated system)
Thomas Tobin et al. (2022)	Biomarker-Based	0–10	Clinical thresholds	Binary (0 = normal, 1 = dysregulated biomarker)

Notes: Physiological System-Based Approach: AL index was scored based on the number of dysregulated physiological systems (each system receives a score of 0 or 1). Biomarker-Based Approach: AL was scored based on the total number of individual biomarkers exceeding predefined cut-off values. Cut-Point Determination: Studies used either population-based quartiles (top or bottom 25 % of sample distribution), clinical thresholds (established medical guidelines), or a combined approach.
Figure Captions

(Ifatunji et al., 2022). For example, Allen et al. (2019) found that racial discrimination across domains was associated with lower AL among individuals who reported coping strategies aligned with the Superwoman Schema (Woods-Giscombé, 2010). This culturally rooted framework emphasizes emotional restraint, resilience, and caretaking in response to systemic adversity and historical expectations placed on Black women (Woods-Giscombe 2010). In the Allen et al. (2019) study, in those reporting racial discrimination, emotional suppression and projecting strength were protective, whereas obligation to succeed and help others increased AL risk (Allen et al., 2019). These findings illustrate how coping can buffer or intensify the physiological toll of discrimination, underscoring the need to move beyond simplistic, linear models (Allen et al., 2019).

Similarly, Mitchell et al. (2020) reported that hopefulness interacted with discrimination in complex ways. Among those who experienced lifetime general perceived discrimination, hopefulness was protective; among those without such experiences, it was associated with higher AL. These findings persisted after adjusting for depressive symptoms and socioeconomic status. Hopefulness may function through diverse pathways, such as proactive coping, enhanced emotional regulation, and health-promoting behaviors, to mitigate stress impacts (Epel et al., 2018; Rodriquez et al., 2019). However, its physiological effects likely vary depending on personal history, social context, and perceived agency (Mitchell et al., 2020).

Discrepant findings may also be related to differences in the type and timing of discrimination measured. Studies using tools that assessed lifetime or landmark events (e.g., Allen et al., 2019; Mitchell et al., 2020) were more likely to find moderated or non-linear effects. In contrast, studies using everyday discrimination measures (e.g., Ong et al., 2017; Van Dyke et al., 2020) tended to find direct associations. This may reflect the more immediate physiological relevance of recent, chronic stressors that align with biomarker collection timing (McEwen, 1998). Everyday discrimination measures also offer greater sensitivity, using frequency and intensity scales that capture cumulative burden, whereas lifetime checklists are more vulnerable to recall bias and adaptation effects (Sheikh et al., 2016). Additionally, subtle, repeated mistreatment may be more difficult to rationalize or cope with, leading to sustained HPA activation (Berger and Sarnyai, 2015). This is supported by a systematic review showing that discrimination is linked to HPA axis dysfunction, depending on timing and chronicity (Busse et al., 2017), as well as broader research linking discrimination to chronic physiological stress (Berger and Sarnyai, 2015; Chen et al., 2023; Juster et al., 2010; McEwen, 2004; Rodriquez et al., 2019).

Across the included studies, we also observed considerable heterogeneity in covariate adjustment. While core demographic factors (age, sex, and education) were consistently included, other important domains such as socioeconomic status, depressive symptoms, perceived stress, coping style, health behaviors, and medication use were variably controlled. This inconsistency in covariate selection may have contributed to the divergent findings across studies, as unmeasured or partially adjusted factors could confound or moderate the discrimination–AL relationship. Establishing a more harmonized approach to covariate adjustment—one that systematically accounts for demographic, psychosocial, and behavioral influences—would improve comparability and strengthen inference across studies in this area.

Establishing consistency in measuring discrimination is an essential point to discuss. Although several validated self-report instruments are commonly used—such as the EDS and *Major Experiences of Discrimination* scale developed by Williams and colleagues, and the EOD instrument by Krieger et al. (2005)—most were originally designed as general measures of unfair treatment and often fail to capture the racialized context of discrimination that disproportionately affects Black adults (Krieger et al., 2005; Williams et al., 1997; Williams et al., 2008). Although these instruments include attribution items (e.g., "Was this because of your race, age, or gender?"), most studies aggregate total scores as an overall indicator of discrimination without analyzing racial attribution separately. In our review, only two studies (Allen et al., 2019; Thomas Tobin et al., 2022) explicitly examined the racial context of discrimination, while others reported general discrimination scores without contextual specification. These mixed findings between studies may reflect differences in sample characteristics, measurement timing, and analytic modeling, but they collectively highlight that discrimination contributing to physiological dysregulation may arise from both race-specific and more generalized experiences of unfair treatment. This underscores the importance of assessing discrimination comprehensively while also contextualizing its source. Recent methodological reviews have emphasized that the use of multi-item, validated scales—rather than single ad hoc questions—produces more reliable and comparable results across studies. National initiatives such as the PhenX Toolkit have begun to standardize these instruments by combining the EDS and Major Experiences scales into a single 19-item protocol with standardized phrasing and attribution prompts (PhenX Toolkit n.d). While consensus has not yet been reached on a universal measure, current best practice recommends employing these validated scales, recording both frequency and attributions of discrimination, and maintaining consistent item wording to facilitate cross-study comparability.

Variation in AL measurement also contributed to inconsistencies across studies. The heatmap comparison (Fig. 2) revealed that studies using broader biomarker panels across more physiological systems (e.g., Ong et al., 2017; Van Dyke et al., 2020) were more likely to detect significant associations. These studies included neuroendocrine (HPA and ANS markers), immunologic, metabolic and cardiovascular markers, which are especially sensitive to chronic psychosocial stress (Cedillo et al., 2020). In contrast, studies with narrower biomarker coverage (e.g., Mitchell et al., 2020; Allen et al., 2019) yielded null or inverse findings. Additionally, the construction of AL indices differed across studies. Some used a physiological system-based scoring approach (e.g., Ong et al., 2017; Van Dyke et al., 2020), while others used a biomarker-count method (e.g., Allen et al., 2019; Thomas Tobin et al., 2022). Each method has advantages and limitations: system-based approaches reflect cumulative system dysregulation, while

biomarker-based scores offer granularity but may miss cross-system interactions (Juster et al., 2010). Scoring thresholds also varied, some used population-based quartiles, others clinical cut-points, or a combination, further complicating comparisons.

To date, no universal "gold-standard" AL index has been established (Beese et al., 2022; Carbone et al., 2022; Juster et al., 2010; McEwen and Akil, 2020). Recent evidence underscores that such variability remains substantial: across U.S. cohort studies—including NHANES analyses—researchers employ markedly different biomarker sets and percentile or clinical cut-points (Duong et al., 2017; Guidi et al., 2021). The most common practice continues to be the use of sample-based quartile thresholds, which ensures within-cohort sensitivity but compromises external comparability (Rodriquez et al., 2019). Alternatively, indices using clinical cut-points grounded in established risk criteria (e.g., blood pressure $\geq$ 130/80 mmHg, HbA1c $\geq$ 6.5 %) improve interpretability and cross-study reproducibility (Allen et al., 2019; Van Dyke et al., 2020). Comparative evaluations suggest that clinically anchored scores perform as well as, or better than, percentile-based methods in predicting downstream health outcomes (McCrory et al., 2023). Moreover, McCrory and colleagues' recent meta-analysis across 13 population-based cohorts identified a parsimonious five-biomarker index—C-reactive protein, resting heart rate, HDL cholesterol, waist-to-height ratio, and HbA1c—that predicted morbidity and mortality equivalently to far more elaborate panels, suggesting a potential pathway toward consensus. Still, methodological innovation continues: item-response and latent-variable models offer promising alternatives to equal-weight summation (Coutinho-Lourenço et al., 2021).

Taken together, contextual, temporal, and measurement differences likely contributed to the heterogeneity and the lack of a significant pooled effect in the meta-analysis. The limited number of eligible studies further reduced statistical power and amplified the impact of variability in study design (e.g., longitudinal vs. cross-sectional), discrimination exposure (e.g., everyday vs. lifetime; racial vs. general), and AL operationalization.

Developmental timing also appears critical. Thomas Tobin et al. (2022) found that exposure to discrimination during adolescence, but not childhood or adulthood, predicted higher AL. This aligns with the lifetime windows of vulnerability theory that highlights the heightened vulnerability to social stressors during brain developmental stages, including adolescence (Lupien et al., 2009; Sisk and Gee, 2022).

In sum, the relationship between discrimination and AL is not uniform. Rather, it is shaped by coping, developmental timing, measurement tools, and physiological pathways. Discrimination may not directly impact biological systems, but it exerts its toll through dynamic interactions with personal, social, and contextual moderators. Understanding this complexity is essential for advancing research on stress, resilience, and health equity among different demographic groups. This review provides a focused and methodologically rigorous synthesis of the discrimination–AL literature in a population historically underrepresented in stress and aging research. By integrating systematic review and meta-analytic approaches with a structured evaluation of study quality and risk of bias, our work not only summarizes existing findings but also highlights key methodological sources of heterogeneity. In doing so, it contributes to a more nuanced understanding of how psychosocial stress becomes biologically embedded across the aging trajectory.

4.1. Limitations and future directions

Several limitations in the existing literature offer important opportunities to advance research on discrimination and biological aging among Black adults. First, many of these studies looking at the association between discrimination and AL have diverse samples but are White majority and do not stratify their analyses by the Black population. This limits the generalizability of findings and reduces the number of studies that directly address the relationship between discrimination and AL in Black middle-aged and older adults, thereby weakening the evidence base for meta-analytic synthesis.

Second, the majority of included studies were cross-sectional, which limits the ability to draw causal inferences about the long-term physiological consequences of discrimination. Longitudinal studies are necessary to assess temporal and cumulative processes by which chronic exposure influences multisystem dysregulation. Third, there was substantial heterogeneity in the methods for measuring AL between studies which involved variance in the biomarker chosen, method of scoring or risk threshold. This lack of standardization complicates cross-study comparability and likely contributes to inconsistent findings. Currently, there is no universally accepted "gold standard" AL index has been established (Beese et al., 2022; McCrory et al., 2023). Although emerging evidence suggests convergence toward clinically anchored cut-points and a core biomarker set (e.g., C-reactive protein, resting heart rate, HDL cholesterol, waist-to-height ratio, HbA1c), further validation across racially and socioeconomically diverse populations is essential to ensure that AL measures equitably reflect cumulative physiological burden.

Variation in how discrimination is measured continues to limit cross-study comparability. Although validated instruments such as the EDS and the EOD scale are frequently employed, their implementation differs in response scaling, attribution coding, and psychometric structure. Future research should prioritize standardized and culturally validated instruments that capture both the frequency and attributions of discrimination, ensuring conceptual and linguistic relevance for diverse Black populations. At the same time, it is essential to recognize that excessive standardization may obscure the contextual and experiential complexity of discrimination, as different forms—such as everyday versus lifetime or attribution-specific versus general perceived discrimination—capture distinct psychosocial processes that may differentially affect health outcomes. Methodological innovations—including Item Response Theory and ecological momentary assessment—offer promising avenues to improve temporal sensitivity and reduce recall bias. Moreover, studies should systematically compare general and attribution-specific discrimination measures within the same samples to determine whether racialized exposures exert stronger or distinct effects on AL. Establishing such cross-instrument validation is a crucial step toward harmonizing measurement frameworks while preserving the conceptual richness necessary to understand the multifaceted nature of discrimination.

Moreover, residual confounding remains a potential source of bias in all reviewed studies. Unmeasured variables such as cumulative socioeconomic adversity, early-life stress, and neighborhood disadvantage may influence both discrimination exposure and AL, complicating causal interpretation. In addition, the lack of consistency in covariate selection and adjustment across studies further limits comparability. Standardizing covariate models—particularly for socioeconomic, psychosocial, and behavioral factors—will be essential for clarifying the independent contribution of discrimination to physiological dysregulation in future research.

The limited number of eligible studies also reduced statistical power and increased the influence of design variability (e.g., cross-sectional vs. longitudinal), measurement differences (e.g., everyday vs. lifetime discrimination), and contextual diversity. Including only five studies in the meta-analysis also constrained the precision and robustness of the pooled effect estimate. Small-scale meta-analyses are inherently more vulnerable to random error and between-study heterogeneity, which can obscure meaningful associations. Thus, the observed null pooled effect should be interpreted with caution, as it may reflect insufficient data rather than the absence of a true association. Finally, the broader underrepresentation of Black populations in stress and health disparities research continues to limit the ability to draw firm conclusions about the discrimination–AL relationship in this group and underscores the need for more inclusive, longitudinal, and methodologically harmonized research.

Further research should address these limitations with standardized, longitudinal and culturally sensitive methods. More specifically, researchers need to develop inclusive (racially) consensus-derived AL indices; employ harmonized measures of discrimination that account for both chronic and acute experiences; and test multilevel models that incorporate coping, psychosocial resilience, social context to enhance understanding of pathways between interpersonal sources of discrimination and physiological dysregulation. This methodological rigor is essential for developing a reproducible, equity-focused science of stress and aging.

5. Conclusion

This study highlights the inconsistent and heterogeneous relationship between discrimination and AL in Black middle-aged and older adults. While existing literature points toward a general trend linking discrimination with increased physiological burden, the evidence remains mixed, with significant variation across study designs, populations, and measurement approaches. Our meta-analysis did not yield a significant pooled effect, reflecting both the limited number of eligible studies and substantial methodological diversity. These findings underscore the need for more rigorous, longitudinal research employing standardized assessment tools and integrating coping and resilience factors to better elucidate the long-term physiological consequences of discrimination and inform the development of tailored interventions.

CRediT authorship contribution statement

Jennifer Deberg: Resources, Methodology. **Jihye Lee:** Formal analysis. **Karen Lawrence:** Validation, Supervision, Methodology. **Lisa L. Barnes:** Writing – review & editing. **Ana W. Capuano:** Writing – review & editing. **Alaa Harb:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Peter B Abad:** Validation, Formal analysis, Data curation. **Juliana Souza-Talarico:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Formal analysis, Conceptualization.

Ethics statement

This study is a systematic review and meta-analysis of published literature and did not involve the collection of new data from human or animal participants. Therefore, institutional review board approval and informed consent were not applicable. All included studies were reviewed to ensure that they reported appropriate ethical approval for their original data collection, in accordance with the Declaration of Helsinki and ethical standards for human research.

Declaration of Generative AI and AI-assisted technologies in the writing process

No generative AI or AI-assisted technologies were used to generate, edit, or interpret scientific content. All content was reviewed and edited by the authors, who take full responsibility for the accuracy and integrity of the manuscript.

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Declaration of Competing Interest

The authors declare no competing interests.

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References

Agbonlahor, O., DeJarnett, N., Hart, J.L., Bhatnagar, A., McLeish, A.C., Walker, K.L., 2024. Racial/ethnic discrimination and cardiometabolic diseases: a systematic review. J. Racial Ethn. Health Disparities 11 (2), 783–807. https://doi.org/10.1007/s40615-023-01561-1.

Allen, A.M., Wang, Y., Chae, D.H., Price, M.M., Powell, W., Steed, T.C., Rose Black, A., Dhabhar, F.S., Marquez-Magaña, L., Woods-Giscombe, C.L., 2019. Racial discrimination, the superwoman schema, and allostatic load: exploring an integrative stress-coping model among African American women. Ann. N. Y Acad. Sci. 1457 (1), 104–127. https://doi.org/10.1111/nyas.14188.

Bailey, Z.D., Krieger, N., Agénor, M., Graves, J., Linos, N., Bassett, M.T., 2017. Structural racism and health inequities in the USA: evidence and interventions. Lancet 389 (10077), 1453–1463. https://doi.org/10.1016/s0140-6736(17)30569-x.

Beese, S., Postma, J., Graves, J.M., 2022. Allostatic load measurement: a systematic review of reviews, database inventory, and considerations for neighborhood research. Int J. Environ. Res Public Health 19 (24). https://doi.org/10.3390/ijerph192417006.

Bell, M.J., Ferraro, K.F., 2025. Intergenerational mobility, race, and allostatic load: diminished health returns for Black older adults? SSMPopul. Health 29, 101750.

Berger, M., Sarnyai, Z., 2015. "More than skin deep": stress neurobiology and mental health consequences of racial discrimination. Stress 18 (1), 1–10. https://doi.org/10.3109/10253890.2014.989204.

Bleich, S.N., Findling, M.G., Casey, L.S., Blendon, R.J., Benson, J.M., SteelFisher, G.K., Sayde, J.M., Miller, C., 2019. Discrimination in the United States: experiences of black Americans. *Suppl 2* Health Serv. Res 54 (2), 1399–1408. https://doi.org/10.1111/1475-6773.13220.

Borenstein, M., Hedges, L.V., Higgins, J.P.T., Rothstein, H.R., 2022. Comprehensive Meta-Analysis (Version 4) [Computer software]. Biostat.

Busse, D., Yim, I.S., Campos, B., Marshburn, C.K., 2017. Discrimination and the HPA axis: current evidence and future directions. J. Behav. Med 40 (4), 539–552. https://doi.org/10.1007/s10865-017-9830-6.

Carbone, J.T., Clift, J., Alexander, N., 2022. Measuring allostatic load: approaches and limitations to algorithm creation. J. Psychosom. Res 163, 111050. https://doi.org/10.1016/j.jpsychores.2022.111050.

Cedillo, Y.E., Lomax, R.O., Fernandez, J.R., Moellering, D.R., 2020. Physiological significance of discrimination on stress markers, obesity, and LDL oxidation among a European American and African American cohort of females. Int J. Behav. Med 27 (2), 213–224. https://doi.org/10.1007/s12529-020-09850-3.

Chen, S., Kertes, D., Benner, A., Kim, S.Y., 2023. Short-term cortisol adaption to discrimination and Mexican-origin adolescents' mental and sleep health. Dev. Psychopathol. 1–13. https://doi.org/10.1017/s0954579423001219.

Cohen, S., Gianaros, P.J., Manuck, S.B., 2016. A stage model of stress and disease. Perspect. Psychol. Sci. 11 (4), 456–463. https://doi.org/10.1177/1745691616646305.

Coutinho-Lourenço, F., Pompéia, S., Cogo-Moreira, H., 2021. On item response theory models in allostatic load scoring. Compr. Psychoneuroendocrinol. 6, 100042. https://doi.org/10.1016/j.cpnec.2021.100042.

Duong, M.T., Bingham, B.A., Aldana, P.C., Chung, S.T., Sumner, A.E., 2017. Variation in the Calculation of Allostatic Load Score: 21 Examples from NHANES. J. Racial Ethn. Health Disparities 4 (3), 455–461. https://doi.org/10.1007/s40615-016-0246-8.

Epel, E.S., 2020. The geroscience agenda: toxic stress, hormetic stress, and the rate of aging. Ageing Res Rev. 63, 101167. https://doi.org/10.1016/j.arr.2020.101167.

Epel, E.S., Crosswell, A.D., Mayer, S.E., Prather, A.A., Slavich, G.M., Puterman, E., Mendes, W.B., 2018. More than a feeling: a unified view of stress measurement for population science. Front Neuroendocr. 49, 146–169. https://doi.org/10.1016/j.yfrne.2018.03.001.

Guidi, J., Lucente, M., Sonino, N., Fava, G.A., 2021. Allostatic load and its impact on health: a systematic review. Psychother. Psychosom. 90 (1), 11–27. https://doi.org/10.1159/000510696.

Higgins, J.P.T., Morgan, R.L., Rooney, A.A., Taylor, K.W., Thayer, K.A., Silva, R.A., Lemeris, C., Akl, E.A., Bateson, T.F., Berkman, N.D., Glenn, B.S., Hróbjartsson, A., LaKind, J.S., McAleenan, A., Meerpohl, J.J., Nachman, R.M., Obbagy, J.E., O'Connor, A., Radke, E.G., Sterne, J.A.C., 2024. A tool to assess risk of bias in non-randomized follow-up studies of exposure effects (ROBINS-E). Environ. Int 186, 108602. https://doi.org/10.1016/j.envint.2024.108602.

Ifatunji, M.A., Faustin, Y., Lee, W., Wallace, D., 2022. Black nativity and health disparities: a research paradigm for understanding the social determinants of health. Int J. Environ. Res Public Health 19 (15). https://doi.org/10.3390/ijerph19159166.

Juster, R.P., McEwen, B.S., Lupien, S.J., 2010. Allostatic load biomarkers of chronic stress and impact on health and cognition. Neurosci. Biobehav Rev. 35 (1), 2–16. https://doi.org/10.1016/j.neubiorev.2009.10.002.

Kessler, R.C., Mickelson, K.D., Williams, D.R., 1999. The prevalence, distribution, and mental health correlates of perceived discrimination in the United States. J. Health Soc. Behav. 40 (3), 208–230.

Krieger, N., Smith, K., Naishadham, D., Hartman, C., Barbeau, E.M., 2005. Experiences of discrimination: validity and reliability of a self-report measure for population health

research on racism and health. Soc. Sci. Med 61 (7), 1576–1596. https://doi.org/10.1016/j.socscimed.2005.03.006.
Lawrence, W.R., Jones, G.S., Johnson, J.A., Ferrell, K.P., Johnson, J.N., Shiels, M.S., Diez Roux, A.V., Forde, A.T., 2023. Discrimination experiences and all-cause and cardiovascular mortality: multi-ethnic study of atherosclerosis. Circ. Cardiovasc Qual. Outcomes 16 (4), e009697. https://doi.org/10.1161/circoutcomes.122.009697.
Lazarus, R.S., Folkman, S., 1984. Stress, Appraisal, and Coping. Springer publishing company.
Lewis, T.T., Everson-Rose, S.A., Powell, L.H., Matthews, K.A., Brown, C., Karavolos, K., Sutton-Tyrrell, K., Jacobs, E., Wesley, D., 2006. Chronic exposure to everyday discrimination and coronary artery calcification in African-American women: the SWAN Heart Study. Psychosom. Med 68 (3), 362–368. https://doi.org/10.1097/01.psy.0000221360.94700.16.
Liberati, A., Altman, D.G., Tetzlaff, J., Mulrow, C., Gøtzsche, P.C., Ioannidis, J.P., Clarke, M., Devereaux, P.J., Kleijnen, J., Moher, D., 2009. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. Ann. Intern. Med. 151 (4), W-65–W-94.
Lupien, S.J., McEwen, B.S., Gunnar, M.R., Heim, C., 2009. Effects of stress throughout the lifespan on the brain, behaviour and cognition. Nat. Rev. Neurosci. 10 (6), 434–445. https://doi.org/10.1038/nrn2639.
McCrory, C., McLoughlin, S., Layte, R., NiCheallaigh, C., O'Halloran, A.M., Barros, H., Berkman, L.F., Bochud, M., E, M.C., M, T.F., Fraga, S., Grundy, E., Kelly-Irving, M., Petrovic, D., Seeman, T., Stringhini, S., Vollenveider, P., Kenny, R.A., 2023. Towards a consensus definition of allostatic load: a multi-cohort, multi-system, multi-biomarker individual participant data (IPD) meta-analysis. Psychoneuroendocrinology 153, 106117. https://doi.org/10.1016/j.psyneuen.2023.106117.
McEwen, B.S., 1998. Stress, adaptation, and disease. Allostasis and allostatic load. Ann. N. Y Acad. Sci. 840, 33–44. https://doi.org/10.1111/j.1749-6632.1998.tb09546.x.
McEwen, B.S., 2004. Protection and damage from acute and chronic stress: allostasis and allostatic overload and relevance to the pathophysiology of psychiatric disorders. Ann. N. Y Acad. Sci. 1032, 1–7. https://doi.org/10.1196/annals.1314.001.
McEwen, B.S., Akil, H., 2020. Revisiting the stress concept: implications for affective disorders. J. Neurosci. 40 (1), 12–21. https://doi.org/10.1523/jneurosci.0733-19.2019.
Miller, H.N., LaFave, S., Marineau, L., Stephens, J., Thorpe Jr., R.J., 2021. The impact of discrimination on allostatic load in adults: an integrative review of literature. J. Psychosom. Res 146, 110434. https://doi.org/10.1016/j.jpsychores.2021.110434.
Mitchell, U.A., Dellor, E.D., Sharif, M.Z., Brown, L.L., Torres, J.M., Nguyen, A.W., 2020. When is hope enough? Hopefulness, discrimination and racial/ethnic disparities in allostatic load. Behav. Med 46 (3-4), 189–201. https://doi.org/10.1080/08964289.2020.1729086.
Moody, M.D., Lewis, J.C.J., 2023. Lifetime vicarious experiences of major discrimination and depressive symptoms among middle-aged and older black adults. Aging Ment. Health 27 (6), 1103–1110. https://doi.org/10.1080/13607863.2022.2117792.
Ong, A.D., Williams, D.R., Nwizu, U., Gruenewald, T.L., 2017. Everyday unfair treatment and multisystem biological dysregulation in African American adults. Cult. Divers Ethn. Minor Psychol. 23 (1), 27–35. https://doi.org/10.1037/cdp0000087.
PhenX Toolkit. (n.d.). Protocol: Discrimination (Major Experiences & Everyday Discrimination Scales). Retrieved October 5, 2025 from ⟨https://www.phenxtoolkit.org/protocols/view/210302#:~:text=The%20Major%20Experiences%20and%20Everyday,religion%2C%20disability%2C%20and%20so%20forth⟩.
Picard, M., Juster, R.P., McEwen, B.S., 2014. Mitochondrial allostatic load puts the 'gluc' back in glucocorticoids. Nat. Rev. Endocrinol. 10 (5), 303–310. https://doi.org/10.1038/nrendo.2014.22.
Polick, C.S., Harris-Gersten, M.L., Dennis, P.A., Noonan, D., Hastings, S.N., Calhoun, P.S., Rosemberg, M.A., Stoddard, S.A., 2024. Allostatic load, morbidity, and mortality among older adults: a multi-wave analysis from the national health and aging trends study. J. Appl. Gerontol. 43 (8), 1052–1059. https://doi.org/10.1177/07334648241230010.
Reid, A.E., Earnshaw, V.A., 2023. Embracing heterogeneity: implications for research on stigma, discrimination, and African Americans' health. Soc. Sci. Med 316, 115111. https://doi.org/10.1016/j.socscimed.2022.115111.
Rodriquez, E.J., Kim, E.N., Sumner, A.E., Nápoles, A.M., Pérez-Stable, E.J., 2019. Allostatic load: importance, markers, and score determination in minority and disparity populations. J. Urban Health 96 (1), 3–11. https://doi.org/10.1007/s11524-019-00345-5.
Sheikh, M.A., Abelsen, B., Olsen, J.A., 2016. Differential recall bias, intermediate confounding, and mediation analysis in life course epidemiology: an analytic framework with empirical example. Front. Psychol. 7, 1828.
Sisk, L.M., Gee, D.G., 2022. Stress and adolescence: vulnerability and opportunity during a sensitive window of development. Curr. Opin. Psychol. 44, 286–292. https://doi.org/10.1016/j.copsyc.2021.10.005.
Sternthal, M.J., Slopen, N., Williams, D.R., 2011. RACIAL DISPARITIES IN HEALTH: how much does stress really matter? Du Bois Rev. 8 (1), 95–113. https://doi.org/10.1017/s1742058x11000087.
Stroup, D.F., Berlin, J.A., Morton, S.C., Olkin, I., Williamson, G.D., Rennie, D., Moher, D., Becker, B.J., Sipe, T.A., Thacker, S.B., 2000. Meta-analysis of observational studies in epidemiology: a proposal for reporting. Jama 283 (15), 2008–2012.
Thomas Tobin, C.S., Gutiérrez, Á., Bell, C.N., Thorpe, R.J., 2022. Early life racial discrimination, racial centrality, and allostatic load among African American older adults. Gerontologist 62 (5), 721–731. https://doi.org/10.1093/geront/gnab185.
Van Dyke, M.E., Baumhofer, N.K., Slopen, N., Mujahid, M.S., Clark, C.R., Williams, D.R., Lewis, T.T., 2020. Pervasive discrimination and allostatic load in African American and white adults. Psychosom. Med 82 (3), 316–323. https://doi.org/10.1097/psy.0000000000000788.
Williams, D.R., 2018. Stress and the mental health of populations of color: advancing our understanding of race-related stressors [review]. J. Health Soc. Behav. 59 (4), 466–485. https://doi.org/10.1177/0022146518814251.
Williams, D.R., Yan, Y., Jackson, J.S., Anderson, N.B., 1997. Racial differences in physical and mental health: socio-economic status, stress and discrimination. J. Health Psychol. 2 (3), 335–351. https://doi.org/10.1177/135910539700200305.
Williams, D.R., Neighbors, H.W., Jackson, J.S., 2003. Racial/ethnic discrimination and health: findings from community studies. Am. J. Public Health 93 (2), 200–208. https://doi.org/10.2105/ajph.93.2.200.
Williams, D.R., Lawrence, J.A., Davis, B.A., Vu, C., 2019b. Understanding how discrimination can affect health. Health Serv. Res 54 (2(2), 1374–1388. https://doi.org/10.1111/1475-6773.13222.
Williams, D.R., Gonzalez, Williams, S., Mohammed, S.A., Moomal, H., Stein, D.J., 2008. Perceived discrimination, race and health in South Africa. Soc. Sci. Med. 67 (3), 441–452. https://doi.org/10.1016/j.socscimed.2008.03.021.
Williams, D.R., Lawrence, J.A., Davis, B.A., 2019a. Racism and health: evidence and needed research. Annu Rev. Public Health 40, 105–125. https://doi.org/10.1146/annurev-publhealth-040218-043750.
Woods-Giscombé, C.L., 2010. Superwoman schema: African American women's views on stress, strength, and health. Qual. Health Res. 20 (5), 668–683.