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ORIGINAL RESEARCH ARTICLE

Discrimination and Health: Does Hiring, Promoting, and Firing Discrimination Relate to Biological Dysregulation and Cardiovascular Disease?

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Abstract

Research on discrimination and health typically examines broad discrimination and cross-sectional health outcomes using subjective self-report measures. We examined three different types of specific job-related discrimination (hiring, promoting, and firing discrimination) and their time-lagged objective health outcomes, specifically biological dysregulation (i.e., allostatic load) and cardiovascular disease. To test hypotheses, we analyzed three waves of MIDUS data (MIDUS II, MIDUS II biomarker project, and MIDUS III). Results showed that discrimination in firing significantly predicted biological dysregulation, while discrimination in hiring and discrimination in promoting did not. In addition, discrimination in hiring, promoting, and firing did not significantly predict general cardiovascular disease. This study sheds light on time-lagged health consequences from specific job-related discrimination in the workplace and underscores the detrimental effect of discrimination in firing on allostatic load in comparison to discrimination in hiring or discrimination in promoting.

Keywords Discrimination · Health · Biological dysregulation · Allostatic load · Cardiovascular disease

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Workplace discrimination is a serious problem (Avery et al. 2008). According to the U.S. Equal Employment Opportunity Commission (EEOC), 84,254 charges related to workplace discrimination were filed in 2017 and secured $398 million for victims (Equal Employment Opportunity Commission 2017). The consequences associated with discrimination are costly for workers and for organizations. Specifically, workers who experience discrimination suffer from psychological and physical strains, and organizations with discrimination issues face expensive lawsuits and bad publicity (Goldman et al. 2006). Given its negative effects on workers and organizations, researchers have considered discrimination as a significant job demand, specifically a hindrance stressor (e.g., Volpone and Avery 2013).

According to the Job Demand-Resources Model (JD-R; Demerouti et al. 2001), job demands, especially hindrances, lead to significant strain (Crawford et al. 2010). In the same vein, discrimination as a hindrance stressor is also expected to yield significant strain outcomes. Consistent with this expectation, numerous studies have demonstrated that people who experience discrimination show more strain than people who do not experience discrimination (e.g., Hammond et al. 2010).

Although researchers have demonstrated the relationship between discrimination and health, the majority of studies have not differentiated distinct types of job-related discrimination (e.g., Avery et al. 2008; De Castro et al. 2008), Thus, our knowledge in regard to distinct types of job-related discrimination and their health outcomes is somewhat limited. Moreover, most job-related research has relied on subjective self-report measures to assess physical and psychological health and has been based on cross-sectional data (e.g., Fox and Stallworth 2005; Krieger et al. 2005). Subjective self-report measures may not accurately portray people's health due to human biases and reporting errors (Donaldson and Grant-Vallone 2002). In addition, cross-sectional data cannot establish temporal precedence between discrimination and health consequences. Hence, it is unclear whether distinct types of job-related discrimination predict future objective physiological health outcomes.

Therefore, we investigate health consequences of distinct types of job-related discrimination (i.e., discrimination in hiring, promoting, and firing). Specifically, we examine biological dysregulation (i.e., allostatic load) and cardiovascular disease outcomes in relation to discrimination in hiring, promoting, and firing. We contribute to the existing literature in several ways. First, we broaden the organizational discrimination literature by investigating relatively understudied outcomes (i.e., allostatic load and heart disease). In addition, we expand the allostatic load literature and the cardiovascular disease literature by examining relations to precise types of organizational discrimination (i.e., discrimination in hiring, promoting, and firing). The combination of precision with regard to organizational discrimination and the understudied objective health outcomes is important as it enables a better understanding of the specific forms of discrimination that may be more or less associated with physiological health-related outcomes. Second, we extend the organizational discrimination literature and the occupational health psychology literature with advanced methodology. In the past, discrimination and health studies mainly relied on subjective self-report measures and cross-sectional data. This is problematic because subjective self-report measures, especially from the same-source, may be vulnerable to biases and cross-sectional data may inflate relationships (e.g., Donaldson and Grant-Vallone 2002). We advance and enhance previous investigations of the relationship between discrimination and health

outcomes by using objective health data based on physiological measures as well as objective self-report measures and by using multiple time point data.

Theoretical Model and Hypotheses

Job Demand-Resources Model and Discrimination

The Job Demand-Resources Model (JD-R; Demerouti et al. 2001) stipulates that job demands and job resources affect employee health and wellbeing. Job demands are "those physical, social, or organizational aspects of the job that require sustained physical or mental effort and are therefore associated with certain physiological and psychological costs (e.g., exhaustion)" (Demerouti et al. 2001, p. 501). Examples of job demands are high workload, organizational constraints, and interpersonal conflicts. On the other hand, job resources refer to "those physical, social, or organizational aspects of the job that may do any of the following: (a) be functional in achieving work goals; (b) reduce job demands and the associated physiological and psychological costs; (c) stimulate personal growth and development" (Demerouti et al. 2001, p. 501). Examples of job resources are supervisor support, job control, and participation in decision making. Initially, the JD-R model suggested two processes. The first process explained how job demands result in exhaustion and the second process indicated how a lack of job resources leads to disengagement. Later, the two limited outcomes were expanded to multiple physical, psychological, or behavioral outcomes (e.g., Hakanen et al., 2008) in order to comprehensively understand the consequences of job demands and job resources.

Job demands are further differentiated into "challenge stressors" and "hindrance stressors" (Crawford et al. 2010; Podsakoff, LePine, & LePine, 2007). Challenge stressors tend to help workers' personal growth and accomplishment (Podsakoff et al., 2007). Examples of challenge stressors are time pressure and work responsibility, and these challenge stressors often produce positive outcomes. On the contrary, hindrance stressors tend to hamper workers' personal development and achievement (Podsakoff et al., 2007). Examples of hindrance stressors are interpersonal conflict and role ambiguity, and the hindrance stressors often lead to negative outcomes.

Based on the JD-R framework, workplace discrimination is considered as a job demand, specifically a hindrance stressor given that it constrains people's development and achievement (e.g., Volpone and Avery 2013). Yet, among different types of hindrance stressors, workplace discrimination may be unique in that it tends to threaten one's core self (e.g., one's self-esteem, Grima 2011; one's self-identity, Shih et al. 2013) not just work progress. Furthermore, workplace discrimination may be more detrimental to employees than other hindrance stressors as workplace discrimination can directly lead to not only loss of emotional resources but also to loss of material resources. Given its seriousness, workplace discrimination is one of the legally forbidden hindrance stressors in the workplace.

Not surprisingly, multiple studies have revealed that workplace discrimination is associated with negative health outcomes. Specifically, Pascoe and Smart Richman (2009) conducted a meta-analytic study and found that perceived discrimination is significantly associated with mental health ($\rho = -.16$) and with physical health ($\rho =$

−.13). More recently, Dhanani et al. (2018) published another meta-analytic study and showed that workplace discrimination is significantly linked to mental health ($\rho = -.29$) and physical health ($\rho = -.19$).

Although the relationships between discrimination and negative health outcomes have been examined, our understanding about the relationships remains limited. First, generally, our understanding is limited to broad discrimination, that is, discrimination that is not specific to any context or is not specific to the type of discriminatory behavior. The majority of studies focused on broad discrimination and examined its effects on health consequences (e.g., Branscombe, Schmitt, & Harvey, 1999; Sanchez & Brock, 1996). However, discrimination may be specific to a domain, such as work or school, and different types of discrimination exist within those domains.

Recently, Dhanani et al. (2018) differentiated discrimination into different types based on its domain (i.e., work vs. nonwork), its nature (i.e., formal vs. interpersonal), its exposure (i.e., experienced vs. observed), and its target (i.e., gender, age, race, and etc.). Among these various types of discrimination, formal discrimination in job decisions such as hiring and promoting needs more attention within organizational science as it is under organizations' control and avoidable with proper rules and regulations compared to other types of discrimination. Also, formal discrimination is expected to be more harmful than other types of discrimination in that formal discrimination may drain not only one's emotional resources but also one's financial resources by losing a promotion or by being fired. Therefore, in order to significantly reduce discrimination in the workplace and minimize its negative consequences, focusing on formal discrimination may be the most effective and fastest way to do so. Furthermore, formal discrimination mainly encompasses discrimination in hiring, promoting, and firing, and investigating the three types of discrimination can yield multiple positive outcomes. First, investigating the three types of discrimination can expand current understanding about the relationship between formal discrimination and health. Second, it can identify whether a certain type of formal discrimination is particularly problematic for people's health and subsequently guide organizations to be more aware of the particular type of discrimination. For these reasons, we investigate discrimination in hiring, promoting, and firing.

Health Indicators: Allostatic Load and Cardiovascular Disease

In the occupational health psychology literature, health outcomes are measured using subjective and/or objective measures (e.g., Theorell et al. 1988). In this study, consistent with past research, we chose allostatic load and presence of cardiovascular disease diagnoses as objective health indicators (e.g., Geronimus et al. 2006; Marmot et al. 1997). Specific hypotheses are presented in the following paragraphs.

Allostatic load has been used as an indicator of prolonged strain (e.g., Geronimus, 2006). Allostatic load represents the efficacy of homeostatic processes and it provides detailed information about aggregated physiological costs from adaptations to stressors (McEwen and Seeman 1999). Stressors can lead to dysregulated physiological systems, and chronic dysregulated physiological systems may cause diseases such as cardiovascular-related disease (Seeman et al. 1997). Specifically, in this study, allostatic load is operationalized as high-risk levels of cardiovascular functioning, glucose metabolism, lipid/fat metabolism, inflammation, hypothalamic pituitary adrenal axis

activity, sympathetic nervous system activity, and parasympathetic nervous system activity.

Although there are a limited number of relevant studies, some studies have showed that discrimination and everyday unfair treatment positively predict allostatic load (e.g., Ong et al. 2017). Similarly, we expect that people who experience more discrimination in hiring, promoting, and firing should have greater allostatic load. Due to the absence of strong theoretical reasons, we do not hypothesize one type of discrimination as more detrimental to allostatic load than the other types. Instead, we explore this as a research question.

Hypothesis 1. Discrimination in hiring positively relates to allostatic load.
Hypothesis 2. Discrimination in promoting positively relates to allostatic load.
Hypothesis 3. Discrimination in firing positively relates to allostatic load.
Research Question 1. Does one type of discrimination more relate to allostatic load than do other types of discrimination?

It is well established that stress contributes to the development of cardiovascular disease (e.g., Cooper and Marshall 2013). In the current study, cardiovascular disease was operationalized as heart disease as indicated by self-reported heart attack, angina, high blood pressure, valve diseases, hole in the heart, blocked artery, irregular heartbeat, heart murmur, heart failure, or other heart-related disease. Researchers have shown that discrimination is linked to heart disease (e.g., Lewis et al. 2006). Following the JD-R framework and empirical findings, we expect that people with discrimination experiences in hiring, promoting, and firing would have a greater incidence of heart disease than people without discrimination experiences in hiring, promoting, and firing. Again, we do not hypothesize one type of discrimination being more detrimental to allostatic load than the other types due to the absence of strong theoretical reasons. Instead, we explore this possibility as a research question.

Hypothesis 4. Discrimination in hiring positively relates to heart disease.
Hypothesis 5. Discrimination in promoting positively relates to heart disease.
Hypothesis 6. Discrimination in firing positively relates to disease.
Research Question 2. Does one type of discrimination more relate to heart disease than do other types of discrimination?

Method

Participants and Procedure

Our study is based on data from the Midlife in the United States (MIDUS) study (Ryff et al. 2012; Ryff et al. 2013; Ryff et al. 2016). MIDUS is a longitudinal study conducted in the United States to investigate patterns, antecedents, and consequences of midlife development among Americans. The nationally representative sample included English-speaking participants residing in the United States. The first wave of MIDUS (MIDUS-I) was collected between 1995 and 1996. The second wave of MIDUS (MIDUS-II) was collected between 2004 and 2006. The third wave of MIDUS

(MIDUS-III) was collected between 2013 and 2014. In the current study, results from MIDUS-II and MIDUS-III were used to examine the proposed hypotheses. As part of MIDUS-II, participants' biomarker data were collected after self-administrated survey data were collected. The average lag between the biomarker data and the self-reported data was 25.87 months (with a range from 1 month to 62 months). In two cases the time lag was 0. In other words, two participants joined MIDUS-II study and MIDUS-II biomarker study at the same time. To ensure temporal precedence from discrimination to allostatic load, we removed these two cases.

For the biomarker data collection, participants visited one of three assigned medical clinics in the United States. After checking-in, participants were asked to report their medical history, participate in physical exams, and answer the self-administered questionnaires (SAQ). Then, from 7 PM to 7 AM, participants were asked to provide urine samples and were offered a room in which to sleep. On the next day, clinic nurses collected fasting blood samples from participants. Before leaving the testing location, participants reported body mass index (BMI), waist-hip ratio, and blood pressure.

A total of 4963 participants completed the MIDUS-II survey. The average age was 55.43 years (SD = 12.45), 47% of them were male, and 91% were white. Of these participants, 1255 returned and participated in the MIDUS-II biomarker project. The average age was 54.50 years (SD = 11.71), 58% were male, and 93% were white. Of 4963 MIDUS-II participants, 3294 returned and completed the MIDUS-III survey. The average age was 63.64 years (SD = 11.35), 45% were male, and 89% were white.

In order to check for potential attrition biases, we performed a series of one-way analyses of variance (ANOVA) and compared participants across the three surveys. Results showed that the three groups were significantly different in age [$F(2, 9508) = 531.09$, $p < .01$], education [$F(2, 9287) = 28.46$, $p < .01$], race [$F(2, 9254) = 5.99$, $p < .01$], and income [$F(2, 7817) = 57.11$, $p < .01$]. Due to potential attrition biases, we only used responses that were completed in both the MIDUS-II survey and the MIDUS-II biomarker survey to test Hypotheses 1–3, and used responses that were completed in the MIDUS-II survey, the MIDUS-II biomarker survey, and the MIDUS-III survey to test Hypotheses 4–6.

Measures

MIDUS-II: Discrimination in Hiring, Promoting, and Firing Discrimination experiences in hiring, promoting, and firing were measured using self-administrated questionnaires in MIDUS II. The item for discrimination in hiring was "In each of the following, indicate how many times in your life you have been discriminated against because of race, ethnicity, gender, age, religion, physical appearance, sexual orientation, or other characteristics. (If the experience happened to you, but for some reason other than discrimination, enter "0") – you were not hired for a job." The item for discrimination in promoting used the same format except that the item asked, "you were not given a job promotion." Similarly, the item for discrimination in firing used the same format except that the item indicated, "you were fired." Responses were based on a frequency interval scale. However, the data were highly positively skewed (skewness ranged from 17.53 to 41.16, kurtosis ranged from 342.95 to 1844.13) and violated the normality assumption of data, which may produce inaccurate results. To handle this non-normal data, we

coded the data as binary (1 = yes, discriminated; 0 = no, not discriminated) to avoid obtaining inaccurate results from the skewed data (Streiner, 2002).

MIDUS-II Biomarker Project: Allostatic Load Allostatic load was assessed using biomarker data. Specifically, allostatic load was calculated using indicators associated with seven physiological risk factor systems for biological dysregulation, following previous studies (e.g., Gruenewald et al. 2012). The seven risk factors and their indicators are cardiovascular functioning (resting diastolic blood pressure, systolic blood pressure, and resting heart rate), glucose metabolism (fasting glucose, glycosylated hemoglobin, and insulin resistance), lipid/fat metabolism (body mass index, waist-to-hip circumference ratio, high-density lipoprotein cholesterol, low-density lipoprotein cholesterol, and triglycerides), inflammation (fibrinogen, plasma C-reactive protein, interleukin-6, intracellular adhesion molecule-1, and the soluble adhesion molecules E-selectin), hypothalamic pituitary adrenal axis activity (urine cortisol and blood dehydroepiandrosterone sulfate hormone), sympathetic nervous system (urine epinephrine and urine norepinephrine), and parasympathetic nervous system (the root mean square of successive differences, the standard deviation of heartbeat-to-heartbeat intervals, low-frequency spectral power, and high-frequency spectral power).

Based on previous studies (e.g., Gruenewald et al. 2012; Ong et al. 2017), a high risk for each biomarker indicator was calculated. Specifically, when participants fell into the high-risk quartile of each biomarker indicator (see Table 1 for specific upper or lower quartile cut-point information), they were assigned a score of 1. Otherwise, they were assigned a score of 0. Then, the scores were averaged in each risk factor. For example, when a participant fell into a high risk quartile of resting diastolic blood pressure (1), but did not fall into high risk quartiles of systolic blood pressure (0) and resting heart rate (0), the score for the cardiovascular functioning risk factor was .333. Lastly, scores of all seven risk factors were summed. The possible range of the final score was from 0 to 7.

MIDUS-III: Heart Disease Participants were asked to report a doctor's remark and opinion about the cause of heart disease as a means to obtain medically objective information using a self-report measure. Specifically, participants were asked to answer the question, "have you ever had heart trouble suspected or confirmed by a doctor?." If yes, they were asked to answer the follow-up questions, "what was the diagnosis?." The available options were heart attack, angina, high blood pressure, valve diseases, hole in the heart, blocked artery, irregular heartbeat, heart murmur, heart failure, and other. When participants reported as having one of these conditions, they were considered as having heart disease. Thus heart disease scores were dichotomous, with 0 indicating no disease and 1 indicating disease.

Covariates Given that sociodemographic variables, medical problems, and health behaviors significantly influence allostatic load and heart disease (e.g., Ford 2013; Gruenewald et al. 2012), we included sociodemographic variables (gender, age, race, education, and income), medical problems (intake of high blood pressure medication, high cholesterol medication, depression medication, and corticosteroid medication), and health behaviors (smoking and drinking problems) as covariates. Additionally, we included time lag as a covariate in case a large range of time lag (a range from 1 month to 62 months) might influence results. Gender was coded as a dichotomous variable

Table 1 Allostatic Load Index

Variables	*N*	*M*	*SD*	Cut-point
Cardiovascular regulation				
Resting SBP (mmHg)	1053	131.11	17.68	≥143.00
Resting DBP (mmHg)	1053	75.05	10.25	≥82.00
Resting heart rate (bpm)	967	72.88	10.81	≥79.70
Metabolic - lipids				
BMI (kg/m2)	1053	29.18	6.01	≥32.31
Waist-to-hip ratio	1052	.89	.10	≥.97.00
Triglycerides (mg/dL)	1045	135.53	139.74	≥160.00
HDL Cholesterol (mg/dL)	1043	54.63	17.60	≤42.00
LDL Cholesterol (mg/dL)	1043	106.31	35.15	≥128.00
Metabolic - glucose metabolism				
Glycosylated hemoglobin	1040	5.99	.92	≥6.12
Fasting glucose (mg/dL)	1039	100.42	24.78	≥104.00
Insulin resistance (HOMA-IR)	1039	3.33	3.65	≥4.07
Inflammation				
Serum C-reactive protein (mg/L)	1040	2.70	4.28	≥3.19
IL6 (pg/mL)	1044	2.79	2.79	≥3.17
Fibrinogen (mg/dL)	1040	340.94	83.74	≥389.75
sE-Selectin (ng/Ml)	1044	41.71	20.99	≥50.58
sICAM-1 (ng/Ml)	1044	287.74	100.76	≥329.42
Sympathetic Nervous System				
Urine Epinephrine (μg/g creatine)	1036	2.04	1.30	≥2.54
Urine Norepinephrine (μg/g creatine)	1042	27.86	13.95	≥33.33
Hypothalamic Pituitary Adrenal Axis				
Urine Cortisol (μg/g creatine)	1051	16.87	26.50	≥20
Blood DHEA-S (μg/dL)	1040	105.44	76.21	≤52.00, ≥144.75
Parasympathetic Nervous System				
R–R interval standard deviation (ms)	967	34.66	17.16	≤23.14
Root mean square successive differences (ms)	967	21.44	17.10	≤11.67
Low-frequency spectral power (ms2)	967	407.86	593.65	≤102.50
High-frequency spectral power (ms2)	967	269.00	671.16	≤51.60

SBP systolic blood pressure, *DBP* diastolic blood pressure, *BMI* body mass index, *HDL* high-density lipoprotein, *LDL* low-density lipoprotein, *IL6* interleukin-6, *sE-Selection* soluble adhesion molecules E-selectin, *sICAM-1* intracellular adhesion molecule-1

(1 = male; 2 = female). Race was also coded as a dichotomous variable (1 = white; 0 = non-white). Education was coded as a categorical variable (1 = no school/some grade school (1–6); 2 = eight grade/junior high school (7–8); 3 = some high school (9–12 no diploma/no GED); 4 = GED; 5 = graduated from high school; 6 = 1 to 2 years of college, no degree yet; 7 = 3 or more years of college, no degree yet; 8 = graduated from 2-year college, vocational school, or associate degree; 9 = graduated from a 4- or

5-year college, or bachelor's degree; 10 = some graduate school; 11 = master's degree; 12 = PH.D., ED.D., MD, DDS, LLB, LLD, JD, or other professional degree). Income was coded as a continuous variable. The medical problem variables (i.e., blood pressure medication, cholesterol medication, corticosteroid medication, and depression medication) were coded as dichotomous variables (1 = Yes; 0 = No) and the health behavior variables (i.e., alcohol problem and smoking) were coded as dichotomous variables (1 = Yes; 0 = No).

Results

Descriptive Statistics and Correlations

Descriptive statistics and intercorrelations for all included variables are presented in Table 2.

Hypotheses Testing

To test Hypotheses 1–3, we performed hierarchical linear regression, specifying allostatic load as a dependent variable. Model 1 included sociodemographic variables and a time lag variable. Model 2 added medication intake variables. Model 3 included health behavior variables. Model 4 included hiring, promoting, and firing discrimination variables. Specific results are presented in Table 3 and a visual representation of the results is provided in Fig. 1.

Results showed that discrimination in hiring ($b = .17$, $p = .06$) and discrimination in promoting ($b = -.02$, $p = .86$) did not significantly predict allostatic load, failing to support Hypotheses 1 and 2. However, discrimination in firing ($b = .24$, $p < .05$) significantly predicted allostatic load, supporting Hypothesis 3. For Research Question 1, we performed a series of z-tests to compare the effects of discrimination across types. Results showed that discrimination in firing more positively predicted allostatic load than did discrimination in hiring ($z = 1.60$, $p < .05$) and discrimination in promoting ($z = 5.79$, $p < .01$). Also, discrimination in hiring more positively predicted allostatic load than did discrimination in promoting ($z = 4.19$, $p < .01$). In other words, the prediction effect of discrimination in firing on allostatic load was *more positive* than the prediction effects of discrimination in hiring and discrimination in promoting on allostatic load; the prediction effect of discrimination in hiring on allostatic load was *more positive* than the prediction effect of discrimination in promoting. Note that when all discrimination variables were included in Model 4, F change became significant (F change = 4.03, $p < .01$), which indicates that discrimination experiences in hiring, promoting, and firing are significantly related to allostatic load beyond the included covariates overall.

For Hypotheses 4–6, logistic regression was performed, specifying heart disease diagnosed by a doctor as a dependent variable. Similar to the earlier hierarchical regression, Model 1 included sociodemographic variables and a time lag variable, Model 2 added medication intake variables, Model 3 included health behavior variable,

Table 2 Descriptive Statistics and Intercorrelations (N = 943–4963)

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Sociodemographic variables																		
1. Age	55.43	12.45	–	–	–	–	–	–	–	–	–	–	–	–	–	–		
2. Gender	1.53	0.50	.00															
3. Race	0.90	0.30	.05**	−.02														
4. Education	7.20	2.52	−.14**	−.10**	.05**													
5. Income	71,364	60,463	−.29**	−.12**	.05**	.35**												
6. Time lag	25.87	14.74	−.15**	.08**	.01	.08**	.06											
Medication use																		
7. Blood pressure medication	0.35	0.48	.33**	.02	−.01	−.08*	−.09**	.01										
8. Cholesterol medication	0.30	0.46	.29**	−.16**	.02	.00	.01	.02	.32**									
9. Corticosteroid medication	0.04	0.20	.00	.03	−.05	−.02	−.03	.11**	.07*	−.01								
10. Depression medication	0.16	0.36	−.03	.10**	.03	.05	−.06	.00	.11**	.10**	.04							
Healthy behaviors																		
11. Alcohol problem	0.04	0.20	−.12**	−.05**	−.01	.04**	.04*	−.02	.00	−.05	.00	.03						
12. Smoking	0.45	0.50	.10**	−.09**	−.02	−.16**	−.11**	−.05	.05	.10**	−.01	.08*	.09**					
Discrimination																		
13. Discrimination in hiring	0.20	0.40	−.10**	−.01	−.07**	.07**	−.01	−.04	−.04	−.05	−.03	.04	.05**	−.07*				
14. Discrimination in promoting	0.16	0.37	−.09**	.01	−.05**	.03*	−.02	.00	.00	.00	.02	.02	.02	−.07*	.46**			
15. Discrimination in firing	0.09	0.29	−.05**	.01	−.08**	−.01	−.05**	−.02	−.04	−.02	.01	.06	.04*	−.11**	.33**	.34**		
Health outcomes																		
16. Allostatic load	1.96	1.06	.30**	−.07*	−.03	−.15**	−.17**	−.08*	.28**	.14**	.03	.09**	−.02	−.05	.05	.03	.09**	
17. Heart disease	0.22	0.41	.24**	−.10**	.01	−.08**	−.07**	−.05	.25**	.19**	.00	.03	−.03	−.06	.00	.02	.03	.15**

* $p < .05$; ** $p < .01$. SD = standard deviation. Gender was coded as 1 (male) and 2 (female). Race was coded as 1 (white) and 0 (non-white)

Table 3 Results of A Hieratical Linear Regression on Allostatic Load

Variables	Allostatic Load			
	Model 1	Model 2	Model 3	Model 4
Sociodemographic variables				
Age	.02 **	.02 **	.02 **	.02 **
Gender (male =1; female =2)	−.15 *	−.18 **	−.18 **	−.20 **
Race (white =1; non-white =2)	−.21	−.19	−.19	−.14
Education	−.05 **	−.05 **	−.05 **	−.05 **
Income	.00 *	.00 *	.00 *	.00
Time lag	.00	.00	.00	.00
Medication use				
Blood pressure medication		.43 **	.43 **	.43 **
Cholesterol medication	–	.03	.03	.03
Corticosteroid medication	–	.11	.11	.13
Depression medication	–	.28 **	.29 **	.27 **
Healthy behaviors				
Alcohol problem	–		.00	.00
Smoking	–	–	−.02	−.05
Discrimination				
Discrimination in hiring	–	–		.17
Discrimination in promoting	–	–		−.02
Discrimination in firing	–	–	–	.24 *
R-square	.115	.164	.164	.175
ΔR-square	–	.049	.000	.011
F-value	20.71 **	18.62 **	15.49 **	13.32 **
F change		13.81 **	0.04	4.03 **

N = 959. *$p < .05$. **$p < .01$. All values are unstandardized coefficients

and Model 4 included hiring, promoting, and firing discrimination variables. Specific results are presented in Table 4.

None of the discrimination variables predicted heart disease; discrimination in hiring ($b = .09$, $p = .75$), discrimination in promoting ($b = -.30$, $p = .26$), and discrimination in firing ($b = -.27$, $p = .40$), failing to support Hypotheses 4–6. Because none of the discrimination variables significantly predicted heart disease, we did not test Research Question 2 (*Does one type of discrimination more relate to heart disease than do other types of discrimination?*).

As an exploratory analysis, we examined whether discrimination in hiring, promoting, and firing significantly predicted specific indicators of heart disease (i.e., heart attack, angina, high blood pressure, valve diseases, hole in the heart, blocked artery, irregular heartbeat, heart murmur, heart failure, and other), and we did not find significant results except for heart failure (see Table 5). In the heart failure results, discrimination in promoting significantly predicted incidence of heart failure ($b = -3.64$, $p < .05$), but all other predictions were non-significant.

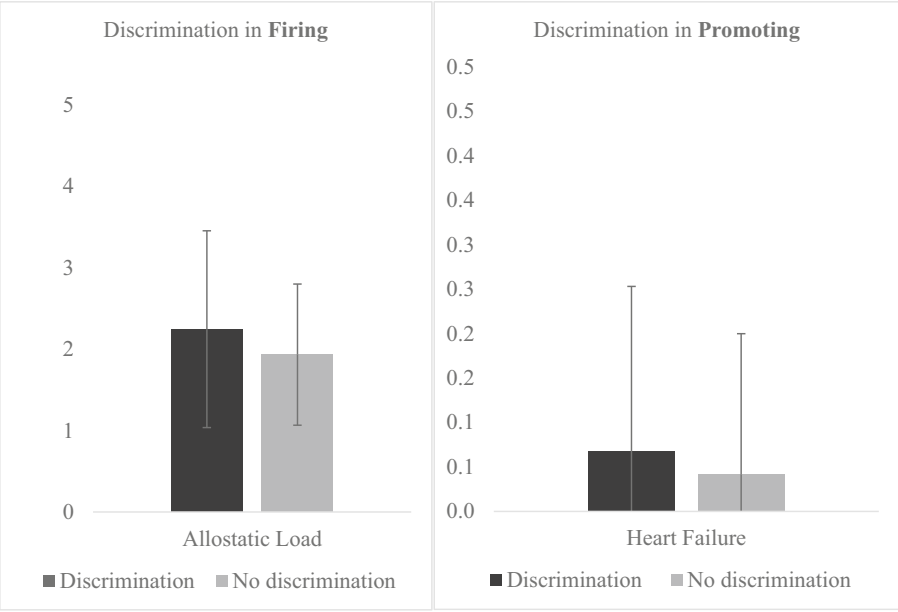

Fig. 1 A significant effect of discrimination in firing on allostatic load and a significant effect of discrimination in promoting on heart failure

Supplemental Analyses

Allostatic Load as a Mediator As a supplemental analysis, we performed a mediation analysis with Mplus 7.4, specifying allostatic load as a mediator of the relationship between discrimination in hiring, promoting, and firing and self-reported heart disease diagnosed by a doctor. Also, we included the significant covariates from the main regression analyses (i.e., age, gender, education, blood pressure medication, and depression medication for allostatic load; age, gender, and blood pressure medication for heart disease). The specified model showed good model fit ($\chi^2(2) = 10.34$, $p < .01$, CFI = 0.96, RMSEA = 0.07). Results are graphically demonstrated in Fig. 2. Similar to the results found across Hypotheses 1–3, discrimination in hiring ($b = .16$, $p = .09$) and discrimination in promoting ($b = .00$, $p = .99$) did not significantly predict allostatic load, while discrimination in firing ($b = .28$, $p < .05$) significantly predicted allostatic load. In addition, discrimination in hiring ($b = -.03$, $p = .57$), discrimination in promoting ($b = .05$, $p = .28$), and discrimination in firing ($b = .03$, $p = .55$) did not significantly predict heart disease, failing to support Hypotheses 4–6. Allostatic load significantly predicted heart disease ($b = .03$, $p < .05$). Lastly, allostatic load did not serve as a significant mediator for the relationship between discrimination in *hiring* and heart disease (.004, $p = .18$), the relationship between discrimination in *promoting* and heart disease (.000, $p = .99$), and the relationship between discrimination in *firing* and heart disease (.008, $p = .11$). Note that without including the covariates, allostatic load served as a significant mediator for the relationship between discrimination in *firing* and heart disease.

Table 4 Results of A Logistic Regression on Heart Disease

Variables	Heart Disease			
	Model 1	Model 2	Model 3	Model 4
Socio-demographic variables				
Age	.05 **	.04 **	.04 **	.04 **
Gender (male =1; female =2)	.47 **	.49 **	.49 **	.52 **
Race (white =1; non-white =2)	.18	.11	.12	.06
Education	−.04	−.04	−.04	−.04
Income	.00	.00	.00	.00
Time lag	.00	.00	.00	.00
Medical variables				
Blood pressure medication	–	−.90 **	−.94 **	−.95 **
Cholesterol medication	–	−.30	−.26	−.26
Corticosteroid medication	–	−.13	−.12	−.10
Depression medication	–	−.16	−.16	−.17
Healthy behaviors				
Alcohol problem	–	–	1.07	1.03
Smoking	–	–	−.20	−.16
Discrimination variables				
Discrimination in hiring	–	–	–	.09
Discrimination in promoting	–	–	–	−.30
Discrimination in firing	–	–	–	−.27
−2 Log likelihood	807.01	775.96	771.44	768.86
Δ-2 Log likelihood		31.05	4.52	2.58
Chi-square	55.46 **	86.51 **	91.03 **	93.62 **
Pseudo R-square	.098	.151	.158	.163

N = 864. *$p < .05$. **$p < .01$. All values are unstandardized coefficients

Time-Lag as a Moderator We examined whether time-lag served as a moderator of the relationships between discrimination in hiring, promoting, and firing and allostatic load. Specifically, we created product terms using define statements and tested the moderating effects on Mplus 7.4. All specified models were just-identified and the model fit was perfect ($\chi^2(0) = 0.00$, $p < .01$, CFI = 1.00, RMSEA = 0.00). Results revealed that time-lag did not moderate the relationship between discrimination in hiring and allostatic load ($b = .01$, $p = .06$), the relationship between discrimination in promoting and allostatic load ($b = .00$, $p = .48$), nor the relationship between discrimination in firing and allostatic load ($b = .00$, $p = .68$). Therefore, it was unlikely that time-lag influenced the relationships between discrimination in hiring, promoting, and firing and allostatic load in this study.

G*ender, Race, and Age as Moderators* We tested whether gender, race, and age moderated the relationships between discrimination in hiring, promoting, and firing and allostatic load. Again, we created product terms using define statements and tested the

Table 5 Results of A Logistic Regression on Heart Disease Caused by A Heart Failure

Variables	Heart Failure			
	Model 1	Model 2	Model 3	Model 4
Sociodemographic variables				
Age	.02	.05	.05	.07
Gender (male =1; female =2)	−1.07	−.72	−.76	−1.21
Race (white =1; non-white =2)	−18.57	−18.52	−18.42	−15.96
Education	−.38 *	−.45 *	−.44 *	−.84 *
Income	.00	.00	.00	.00
Time lag	.04	.03	.03	.03
Medical variables				
Blood pressure medication	–	−.19	−.21	−.40
Cholesterol medication	–	−.18	−.11	−.80
Corticosteroid medication	–	−1.33	−1.33	−.80
Depression medication	–	−2.30 *	−2.28 *	−4.42 *
Healthy behaviors				
Alcohol problem	–	–	17.70	17.43
Smoking	–	–	−.16	.70
Discrimination variables				
Discrimination in hiring	–	–	–	−1.27
Discrimination in promoting	–	–	–	−3.64 *
Discrimination in firing	–	–	–	21.80
−2 Log likelihood	47.58	41.28	41.04	30.54
Δ-2 Log likelihood		6.30	0.24	10.50
Chi-square	10.79	17.08	17.33	27.83 *
Pseudo R-square	.212	.329	.333	.520

N = 170. *$p < .05$. **$p < .01$. All values are unstandardized coefficients

moderating effects on Mplus 7.4. All specified models were just-identified and the model fit was perfect ($\chi^2(0) = 0.00$, $p < .01$, CFI = 1.00, RMSEA = 0.00). Results showed that gender did not moderate the relationship between discrimination in hiring and allostatic load ($b = -.03$, $p = .86$), the relationship between discrimination in promoting and allostatic load ($b = .04$, $p = .83$), nor the relationship between discrimination in firing and allostatic load ($b = -.01$, $p = .98$). Also, race did not moderate the relationship between discrimination in hiring and allostatic load ($b = -.22$, $p = .43$), the relationship between discrimination in promoting and allostatic load ($b = -.08$, $p = .79$), nor the relationship between discrimination in firing and allostatic load ($b = -.22$, $p = .51$). Finally, results demonstrated that age did not moderate the relationship between discrimination in hiring and allostatic load ($b = -.01$, $p = .38$), the relationship between discrimination in promoting and allostatic load ($b = -.08$, $p = .79$), nor the relationship between discrimination in firing and allostatic load ($b = -.02$, $p = .07$). In sum, it appears that gender, race, and age did not influence the relationships between discrimination in hiring, promoting, and firing and allostatic load in this study.

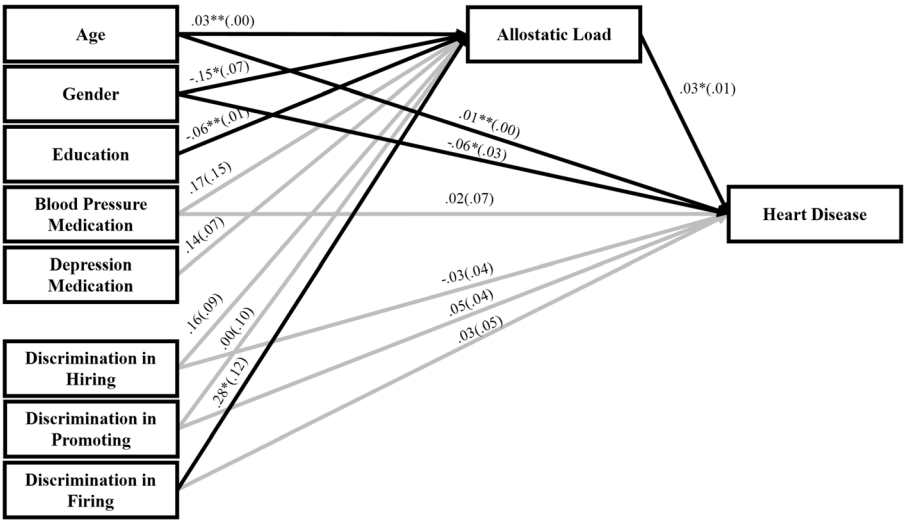

Fig. 2 A mediation model (allostatic load as a mediator and heart disease as an outcome). *Note.* *$p < .05$. **$p < .01$. All values are unstandardized coefficients

Discrimination as a Mediator We also considered that controlling for age, race, and gender in our hypothesis testing may have removed meaningful variance in discrimination and consequently diminished the estimates of discrimination given that age, race, and gender are risk factors for the experience of discrimination (e.g., Colella et al. 2017). Therefore, we conducted additional path analyses specifying age, race, and gender as independent variables, discrimination in hiring, promoting, and firing as mediators, and health outcomes as dependent variables. As the three types of discrimination are expected to be related, we included intercorrelation terms between the three types of discrimination in the path analyses.

First, we specified *allostatic load* as an outcome variable and obtained perfect model fit ($\chi^2(0) = 0.00$, $p < .01$, CFI = 1.00, RMSEA = 0.00). Specific results are presented in Fig. 3. Results showed that age and race significantly predicted discrimination in hiring, discrimination in promoting, and discrimination in firing, indicating that older individuals and non-white individuals reported more discrimination. In addition, age, race, and discrimination in firing directly predicted allostatic load, suggesting that increased age, non-white individuals, and more discrimination in firing were related to great allostatic load. In terms of the mediation effects, the total indirect effect from *age* to allostatic load was significant (−.00, $p < .05$) and specifically discrimination in firing served as a significant mediator in the relationship (.00, $p < .05$). Also, the total effect was significant (.03, $p < .01$). Next, the total indirect effect from *race* to allostatic load was significant (−.03, $p < .01$) and specifically discrimination in firing served as a significant mediator in the relationship (−.02, $p < .05$). The total effect was also significant (−.27, $p < .05$). Lastly, the total indirect effect from *gender* to allostatic load was not significant (.00, $p = .99$) and none of the discrimination variables served as a significant mediator in the relationship. Also, the total effect was not significant (−.12, $p = .051$). Note that the direct effect from *age* to discrimination in firing was significantly positive and the direct effect from discrimination in firing to allostatic load was significantly positive, resulting in the positive indirect effect of age on allostatic load

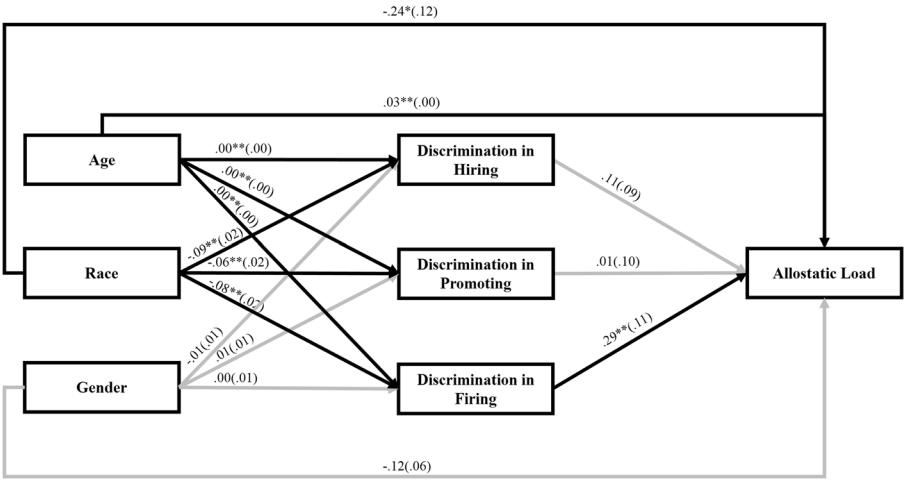

Fig. 3 A mediation model (the three types of discrimination as mediators and allostatic load as an outcome) *p < .05. **p < .01. All values are unstandardized coefficients

via discrimination in firing and suggesting that increasing age was associated with more discrimination in firing which was then associated with greater allostatic load. Consistently, the direct effect from age to allostatic load was also significantly positive. In addition, the direct effect from *race* to discrimination in firing was significantly negative and the direct effect from discrimination in firing to allostatic load was significantly positive, resulting in the negative indirect effect of race on allostatic load via discrimination in firing and indicating that non-white individuals reported more discrimination in firing which then was associated with greater allostatic load. The direct effect from race to allostatic load was also significantly negative.

Second, we specified *heart disease* as an outcome variable and obtained perfect model fit ($\chi^2(0) = 0.00$, $p < .01$, CFI = 1.00, RMSEA = 0.00). Specific results are shown in Fig. 4. Results revealed that age and race significantly predicted discrimination in *hiring,* discrimination in *promoting,* and discrimination in *firing* such that older individuals and non-white individuals reported more discrimination. In addition, age and gender significantly predicted heart disease, such that increasing age and male gender were associated with greater incidence of heart disease. As for the mediation effects, the total indirect effect from *age* to heart disease was significant (.00, $p < .05$); however, none of the discrimination types served as a significant mediator in the relationship. Note that the total effect was significant (.01, $p < .01$). In addition, the total indirect effect from *race* to heart disease was significant (−.01, $p < .05$); yet, none of the discrimination types served as a significant mediator in the relationship. The total effect was not significant (.00, $p = .95$). Lastly, the total indirect effect from *gender* to heart disease was not significant (.00, $p = .54$) and none of the discrimination types served as a significant mediator in the relationship. The total effect was significant (−.08, $p < .01$).

Two-Way Interactions between Discrimination in Hiring and Promoting In the hierarchical regression and logistic regression results, the effects of discrimination in hiring and discrimination in promoting were not significant. One possibility is that the two

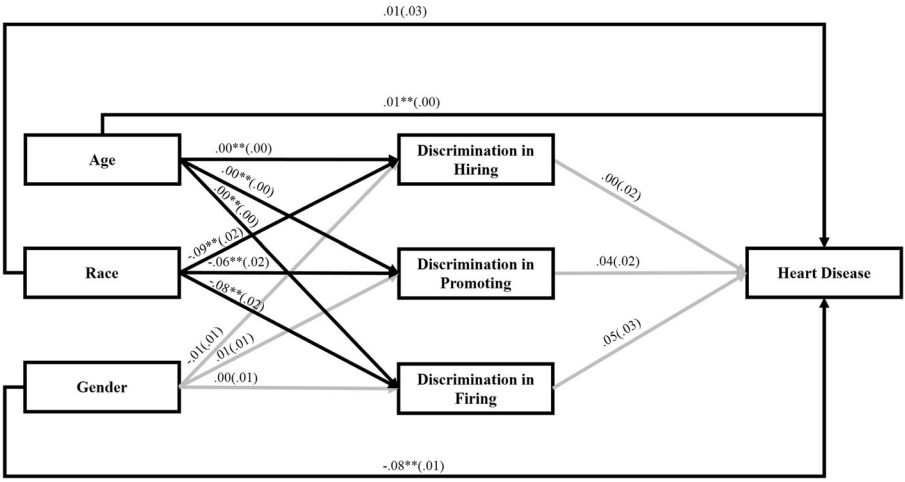

Fig. 4 A mediation model (the three types of discrimination as mediators and heart disease as an outcome). *$p < .05$. **$p < .01$. All values are unstandardized coefficients

types of discrimination might interact with each other and affect the results. Therefore, we performed two-way interaction analyses based on the two variables, discrimination in hiring and discrimination in promoting. Specifically, we created an interaction product term using a define statement and tested the interaction effects on Mplus 7.4. First, when allostatic load was specified as an outcome variable, results showed perfect model fit ($\chi^2(0) = 0.00$, $p < .01$, CFI = 1.00, RMSEA = 0.00). Results revealed that discrimination in hiring ($b = .10$, $p = .38$), discrimination in promoting ($b = .05$, $p = .71$), and the interaction between discrimination in hiring and in promoting ($b = -.01$, $p = .95$) were not significant on allostatic load.

Next, we specified heart disease as an outcome variable. Because heart disease was a binary outcome, a logistic regression was performed and model fit information was not produced. Results showed that discrimination in hiring ($b = -.17$, $p = .31$), discrimination in promoting ($b = .04$, $p = .83$), and the interaction effect between discrimination in hiring and promoting ($b = .28$, $p = .32$) were not significant on heart disease.

Three-Way Interactions among Discrimination in Hiring, Promoting, and Firing Moreover, it is also possible that all three types of discrimination (i.e., discrimination in hiring, discrimination in promoting, and discrimination in firing) might interact with each other and affect the results in allostatic load and heart disease. Therefore, we conducted three-way interaction analyses among the three types of discrimination. Again, we created an interaction product term using a define statement and tested the interaction effects in Mplus 7.4. When allostatic load was specified as an outcome variable, we found perfect model fit ($\chi^2(0) = 0.00$, $p < .01$, CFI = 1.00, RMSEA = 0.00). Results revealed that discrimination in hiring ($b = .08$, $p = .57$) discrimination in promoting ($b = -.02$, $p = .90$) did not show significant main effects; yet, discrimination in firing ($b = .58$, $p < .05$) demonstrated a significant main effect. In terms of interaction effects, none of the interaction effects were significant. Specifically, the interaction between discrimination in hiring and discrimination in promoting was not significant ($b = .15$, $p = .54$); the interaction between discrimination in hiring and

discrimination in firing was not significant ($b = -.18$, $p = .61$); the interaction between discrimination in promoting and discrimination in firing was not significant ($b = -.18$, $p = .65$); the interaction between all discrimination in hiring, discrimination in promoting, and discrimination in firing was not significant ($b = -.32$, $p = .53$).

Next, we specified heart disease as an outcome variable. Because heart disease was a binary outcome, a logistic regression was performed and model fit information was not yielded. Results showed that none of the main effects were significant on heart disease (discrimination in hiring: $b = -.21$, $p = .24$; discrimination in promoting: $b = .07$, $p = .74$; discrimination in promoting: $b = .29$, $p = .28$). Also, none of the interaction effects were significant. Specifically, the interaction between discrimination in hiring and discrimination in promoting was not significant ($b = .29$, $p = .37$); the interaction between discrimination in hiring and discrimination in firing was not significant ($b = .09$, $p = .86$); the interaction between discrimination in promoting and discrimination in firing was not significant ($b = -.56$, $p = .38$); the interaction between all discrimination in hiring, discrimination in promoting, and discrimination in firing was not significant ($b = .23$, $p = .78$).

Discussion

Based on the JD-R model, the current study investigated the effects of discrimination in hiring, promoting, and firing on biological dysregulation (i.e., allostatic load) and cardiovascular disease (self-reported heart disease diagnosed by a doctor). Results showed that discrimination in firing positively predicted allostatic load, while discrimination in hiring and discrimination in promoting did not. We speculate that this is because being fired drastically reduces life resources including financial, emotional, and interpersonal resources (Cartwright and Cooper 1997) to a greater degree than does not being hired or not being promoted. In addition, being fired would require greater adaptation than not being hired or not being promoted. Due to the higher stakes involved in being fired, people who experienced discrimination in a firing situation might show higher allostatic load than people who experienced discrimination in hiring or promoting. Another possible explanation is that people who reported that they were discriminated in a firing situation who experience actual job loss could have their allostatic load impacted, irrespective of discrimination.

In addition, discrimination in hiring, promoting, and firing did not significantly predict incidence of heart disease. One possible explanation is that the time lag used in the current study may be too short of a follow up period to detect significant findings. Heart disease develops over the course of decades and stress is only one factor that contributes to its development. Alternately, heart disease can refer to any number of multiply-determined cardiovascular disorders such as narrowing of cardiac vessels, angina, heart attack, valve abnormalities, some arrhythmias, and some forms of stroke, each with its own etiology, making the term “heart disease” somewhat fuzzy. Assessment of specific cardiovascular disorders would have provided a more precise estimate of the presence and extent of heart disease. Allostatic load prospectively predicts cardiovascular disease incidence, but the most consistent findings predict all-cause mortality (Juster et al. 2010). Thus, our measure of disease outcome may have been too specific to show associations with allostatic load.

We also examined the effects of discrimination in hiring, promoting, and firing on specific manifestations of heart disease. Experiencing discrimination in promoting significantly predicted future heart failure. However, this finding should be interpreted with caution because discrimination in promoting was not associated with any other form of heart disease and there is no reason to expect that the experience of discrimination would be specific to heart failure over other manifestations of heart disease.

In the supplemental analyses, we tested the mediation effects of allostatic load on the relationships between discrimination in hiring, promoting, and firing and self-reported health disease diagnosed by a doctor. First, results revealed that discrimination in firing significantly predicted allostatic load, while discrimination in hiring and discrimination in promoting did not. Note that the findings were consistent with the results from hierarchical linear regression. Also, all discrimination in hiring, discrimination in promoting, and discrimination in firing did not significantly predict heart disease, supporting the results based on logistic regression. Yet, allostatic load significantly predicted heart disease diagnosed by a doctor. This is consistent with the allostatic load model argument that allostatic load leads to abnormal physiological fluctuations and eventually manifests chronic diseases (Juster et al. 2010; McEwen and Seeman 1999).

Our moderation analyses showed that time lag did not moderate the relationship between discrimination and allostatic load. It indicates that different time lags between participants did not influence the results in regard to the relationship between discrimination and allostatic load. In addition, we examined whether gender, race, and age moderated the relationship between discrimination and allostatic load. We found that they did not moderate the relationship.

Next, we conducted additional path analyses, considering gender, age, and race as independent variables, the three types of discrimination as mediators, and allostatic load (or heart disease) as a dependent variable. In general, it appears that age and race are more significant risk factors for the experience of discrimination in hiring, promoting, and firing than is gender. It is surprising that gender was found to be a not strong risk factor, despite the fact that multiple studies show women in the United States experience more discrimination than do men (e.g., Colella et al. 2017). Specifically, multiple studies reveal that women are treated unfavorably in career decisions, and consequently they get promoted 15% less (Yee et al. 2016) and get paid 21.7% less (Hegewisch and Hartmann 2014) than men. Even within this data, women had a lower income than did men, suggesting that the wage gap existed. It may be that women are more hesitant to admit that they were discriminated or report that they were discriminated than were men. The results might indicate that there is a need to foster an environment where all minorities especially women can admit and report their discrimination incidents without worrying about negative consequences.

As the last supplemental analyses, we examined whether the different types of discrimination interacted with each other. Results showed that the two-way interaction effect was not significant for allostatic load or for heart disease. Moreover, the interactions among discrimination in hiring, discrimination in promoting, and discrimination in firing did not seem to affect the results in allostatic load and heart disease.

In summary, the findings in this study support the claim of JD-R model that a hindrance stressor impairs people' health (Crawford et al. 2010; Demerouti et al. 2001). Furthermore, the findings indicate that even among the similar nature of hindrance stressors (i.e., discrimination in hiring, promoting, and firing), the effects for allostatic

load vary by types of discrimination. Specifically, discrimination in firing appears to be more detrimental to allostatic load than do discrimination in hiring and discrimination in promoting.

Strengths, Limitations, and Future Research

One strength of this study is that it examined different job-related types of discrimination and showed different effects on health. This investigation broadens current understanding about the relationship between discrimination and health and calls for more future research on specific types of discrimination. Second, we used objective measures and reveals unique information that subjective measures failed to find, which is that discrimination in firing may be more detrimental to biological dysregulation than discrimination in hiring and promoting. This finding emphasizes the importance of incorporating objective measures especially for heavily perception-driven constructs. Additionally, this study is based on a large, nationally representative sample.

This study also has some limitations. First, discrimination in hiring, promoting, and firing was measured using self-reported responses to a single item for each type of discrimination. We encourage future researchers to replicate our findings using multiple items of discrimination in hiring, promoting, and firing and measuring richer information about discrimination such as the nature of discrimination incidents. Second, although objective heart disease information was collected, it was obtained through self-report and not medical record review. Third, we did not have allostatic load information before discrimination was experienced; therefore, we could not compare levels of allostatic load before and after discrimination within individuals. We encourage future researchers to obtain strain information *before* and *after* discrimination time points. Performing both within-person and between-person comparisons may provide additional valuable information. Lastly, based on the current study, we recommend improvements in both the scope and the methodological approach of research and further exploration of the effect of discrimination in human resource practices such as training and compensation.

Practical Implications

These findings are useful to organizations in that they help underscore the damaging effects of workplace discrimination on employee physiological health. Although organizations should attempt to reduce all types of discrimination, they may want to focus first on discrimination in firing given its significant effects on employee allostatic load. We believe that this information will be even more beneficial to organizations that have limited resources but want to decrease discrimination issues in the workplace.

Conclusion

We investigated different types of job-related discrimination (i.e., discrimination in hiring, promoting, and firing) and their time-lagged objective health consequences (i.e., allostatic load and heart disease). Results revealed that discrimination in firing significantly predicted allostatic load, while discrimination in hiring and promoting did not. The findings suggest that discrimination in firing may be more detrimental to people's

health in comparison to discrimination in hiring or promoting and call for additional research in discrimination in specific settings. In addition, we found that discrimination in hiring, promoting, and firing did not significantly predict heart disease diagnosed by a doctor. Although the results related to heart disease were not significant, this may be due to limitations present in the current data such as the coarse and skewed assessment of discrimination. We encourage future researchers to further investigate the relationships between different types of discrimination and specific types of heart disease. This study sheds light on time-lagged objective health consequences of specific job-related types of discrimination in the workplace, and highlights the need to examine discrimination in specific settings and its effects on their physiological health.

Appendix

Archival Data Set Information

We used three archival datasets, Midlife in the United States (MIDUS)-II, MIDUS-II Biomarker Project, and MIDUS-III. With the MIDUS data, the specific types of job-related discrimination (i.e., discrimination in hiring, promoting, and hiring) have not been investigated in any previous or current articles.

Project Title: Midlife in the United States (MIDUS) Series.

Principal Investigator(s):

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MIDUS-II Biomarker Project: Carol D. Ryff, University of Wisconsin-Madison; Teresa Seeman, University of California-Los Angeles; Maxine Weinstein, Georgetown University.

MIDUS-III: Carol Ryff, University of Wisconsin-Madison; David Almeida, Pennsylvania State University; John Ayanian, University of Michigan; Neil Binkley, University of Wisconsin-Madison; Deborah S. Carr, Rutgers University; Christopher Coe, University of Wisconsin-Madison; Richard Davidson, University of Wisconsin-Madison; Joseph Grzywacz, Florida State University; Arun Karlamangla, University of California-Los Angeles; Robert Krueger, University of Minnesota; Margie Lachman, Brandeis University; Gayle Love, University of Wisconsin-Madison; Marsha Mailick, University of Wisconsin-Madison; Daniel Mroczek, Northwestern University; Barry Radler, University of Wisconsin-Madison; Teresa Seeman, University of California-Los Angeles; Richard Sloan, Columbia University; Duncan Thomas, Duke University; Maxine Weinstein, Georgetown University; David Williams, Harvard University.

Link to the official website: http://midus.wisc.edu/

Link to the dataset:

MIDUS-II: https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/4652/datadocumentation

MIDUS-II Biomarker Project: https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/29282/datadocumentation

MIDUS-III: https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/36346/datadocumentation

Link to a bibliography of published works from the dataset:

MIDUS-II: https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/4652/publications

MIDUS-II Biomarker Project: https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/29282/publications

MIDUS-III: https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/36346/publications

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MIDUS-II Biomarker Project: United States Department of Health and Human Services. National Institutes of Health. National Institute on Aging (P01-AG020166).

MIDUS-III: United States Department of Health and Human Services. National Institutes of Health. National Institute on Aging (PO1AG020166).

Bibliographic Citation:

MIDUS-II: Ryff, Carol, Almeida, David M., Ayanian, John, Carr, Deborah S., Cleary, Paul D., Coe, Christopher, … Williams, David. Midlife in the United States (MIDUS 2), 2004–2006. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2017-11-20. https://doi.org/10.3886/ICPSR04652.v7

MIDUS-II Biomarker Project: Ryff, Carol D., Seeman, Teresa, and Weinstein, Maxine. Midlife in the United States (MIDUS 2): Biomarker Project, 2004–2009. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2018-10-31. https://doi.org/10.3886/ICPSR29282.v8

MIDUS-III: Ryff, Carol, Almeida, David, Ayanian, John, Binkley, Neil, Carr, Deborah S., Coe, Christopher, … Williams, David. Midlife in the United States (MIDUS 3), 2013–2014 . Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2017-11-21. https://doi.org/10.3886/ICPSR36346.v6

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