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RESEARCH ARTICLE

Age Differences in Physiological Reactivity to Daily Emotional Experiences

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Abstract

How does physiological reactivity to emotional experiences change with age? Previous studies addressing this question have mostly been conducted in laboratory settings during which emotions are induced via pictures, films, or relived memories, raising external validity questions. In the present research, we draw upon two datasets collected using ecological momentary assessment methods (totaling 134,723 daily reports from 14,436 individuals) to examine age differences in heart rate (HR) and blood pressure (BP) reactivity to naturally occurring emotional experiences. We first examined how older and younger individuals differ in the prevalence of emotions varying in valence and arousal. On average, people reported experiencing positive emotions (high or low arousal) more than 70% of the time they were asked, and older (vs. younger) individuals tended to report positive emotions more frequently. In terms of physiological reactivity, we found that age was associated with reduced HR and BP reactivity. Some evidence was also found that the magnitude of such age differences may depend on the valence or arousal of the experienced emotion. The present findings have implications for understanding how emotions can contribute to physical health across the lifespan.

Keywords Aging · Emotions in daily life · Autonomic nervous system · Cardiovascular reactivity

Emotional experiences are accompanied, if not defined (Levenson, 1999), by changes in autonomically-mediated physiological responses (James, 1884; Joseph et al., 2021; Kreibig, 2010). Yet, the extent to which physiological changes occur in response to emotions can differ as a function of context, fitness, and importantly, age (Mendes, 2010; Shiota & Neufeld, 2014; Stemmler et al., 2001). In this research, we draw upon two datasets (totaling 134,723 daily reports from 14,436 individuals) collected using ecological momentary assessment (EMA) to examine the prevalence of emotions differing in valence and arousal, the strength of the associations of emotions with physiological responses, and how age is linked with prevalence of and physiologic responses to emotions.

Emotions in Daily Life

With the advancement in experience sampling methodology, considerable research has examined people's emotional experiences in their natural environment (e.g., Hoemann et al., 2020; Moeller et al., 2020). These studies have shown that people generally feel more positive emotions than negative ones in daily life (Barford et al., 2020; MacCann et al., 2020), and particularly experience emotions such as "happiness" and "satisfied" to a great degree (Lucas et al., 2021). Although promising, most previous work has relied on relatively small samples with little variability in terms of age (primarily undergraduate samples). Exceptionally, Trampe and colleagues (2015) collected real-time emotion data from a large sample ($N > 10{,}000$) using a mobile application. They found that 41% of the time participants reported experiencing *any* emotions, they were experiencing positive emotions; 16% of the time, they were experiencing negative emotions,

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and 33% of the time, they were experiencing at least one of both positive and negative emotions.

Not addressed in this work was how age differences manifest in daily emotional experiences. Indeed, there are theoretical reasons to believe that younger and older individuals differ in which emotions they experience in everyday life (Scheibe & Carstensen, 2010); empirical data on daily emotional experiences also suggest that older (vs. younger) individuals tend to report more positive and less negative emotions (English & Carstensen, 2014; Klaiber et al., 2021; Mak & Schneider, 2022). However, not all empirical work has evidenced the same age effect. One experience sampling study found no differences in positive emotional experiences across age groups (Puente-Martínez et al., 2021) and another found age-related increases in positive emotional experiences but only ones characterized by low arousal (Scheibe et al., 2013; also see Hamm et al., 2021). Building on this body of work, our research examines age differences in the prevalence of emotions differing in valence and arousal in two large datasets, aiming to obtain more robust and generalizable estimates.

Research on Age Differences in Physiological Reactivity to Emotions

When examining physiological responses to emotions, most research has induced emotions via pictures, films, relived memories, or standardized social interactions in laboratory settings. Consistent with the idea that mind-body connections become weaker in late life (Mendes, 2010) partly due to structural and functional changes in the autonomic nervous system (Cacioppo et al., 1998; Shiota & Neufeld, 2014), many studies have found age-related declines in physiological reactivity, particularly heart rate (HR) reactivity, to emotions. For example, older (vs. younger) adults showed smaller HR reactivity while watching an amusing film (Tsai et al., 2000), recalling angry or happy memories (Labouvie-Vief et al., 2003), or an evaluative task evoking negative affect (Mikneviciute et al., 2023; Wrzus et al., 2014). Nevertheless, not all structural changes associated with aging affect reactivity in the same way. Increased stiffness of the large arteries, for example, can lead to increased resting blood pressure (BP; Pinto, 2007) and BP reactivity to emotions. Indeed, Uchino et al.'s (2010) meta-analysis showed that age was generally associated with greater systolic BP (SBP) reactivity to laboratory tasks, including emotion induction tasks.

Although valuable, laboratory findings offer limited insights into how age differences in physiological reactivity manifest in real life given their reduced ecological validity (Wilhelm & Grossman, 2010). For example, younger and older individuals likely differ in what type of emotions they typically experience and in response to which situations (Riediger & Rauers, 2014). Thus, using the same stimuli to induce emotions overlooks any potential effects that the *relevance* of experimental stimuli has on physiological reactivity (Velasco & Bond, 1998). More broadly, laboratory studies may be limited in capturing the processes underlying age differences in daily emotional lives. Theoretical frameworks such as the model of strength and vulnerability integration (Charles, 2010; Charles & Piazza, 2009) consider the enhanced use of emotion regulation strategy (i.e., age-related strengths) and reduced physiological regulatory capacity (i.e., age-related vulnerabilities) as jointly contributing to age differences in emotional lives. However, laboratory procedures may not precisely reflect real-life emotion regulatory processes (Isaacowitz, 2022) and affect the observed emotional experiences and physiologic reactivity.

Overview

We examined how age moderated the prevalence of and physiologic reactivity to naturally occurring emotions. We focused on two broad features of emotions, valence and arousal, considering that one rarely experiences one specific emotion exclusively in daily life (on average, our participants experienced more than three discrete emotions simultaneously; see the Supplemental Materials). Thus, not only is isolating physiologic reactivity to a specific emotion challenging in real life, but single-emotion experiences may not be the most representative of daily life experiences.

For physiologic reactivity (i.e., changes), we examined HR and BP. In natural environments, there is no "baseline" equivalent to that in the laboratory settings where physiologic activity is assessed before and after an emotion induction, then change scores are calculated. The purpose of baseline assessment is to estimate the person's "resting" state to then capture how much a stimulus/event changes it. To mimic the laboratory strategy, albeit imperfectly, we identified the check-in with the lowest HR as a proxy for the resting state and used the BP values from that check-in as our "baseline" responses.

Method

Participants and Procedure

Data for the present research were collected via MyBPLab (https://mybplab.com), a mobile application that could be downloaded from the Google Play Store (see Gordon & Mendes, 2021). We analyzed data from two versions of this app: Sample A refers to participants of MyBPLab V2.0 (data collected from March 2019 to December 2021); Sample B refers to participants of MyBPLab V1.0 (data collected from January 2018 to December 2019). The key difference between the two samples relevant to this research is that

emotion was assessed every third day for Sample A and every day for Sample B (resulting in a larger number of observations in Sample B). Individuals who downloaded the app (requiring a phone or watch with a built-in optic sensor used to measure and estimate HR and BP), were 18 years or older, and passed a short English fluency quiz were asked to participate in a 21-day study. Upon enrollment, participants were instructed to calibrate the optical sensor using an external BP device to estimate BP. The sensor collects finger photoplethysmography (PPG) signals that are being widely used to measure various cardiovascular parameters (see Elgendi et al., 2019 for details on the specifics of PPG-based BP assessments). Table 1 provides the demographic characteristics of participants in each sample.

Every day, participants received notifications to complete a check-in. They could complete up to three daily check-ins that included a set of questionnaires (one in each of the three time windows: 7am – 10am [morning], 10am – 4pm [afternoon], 8pm – 11pm [evening]). At every check-in, participants placed their index finger over the optical sensor on the phone or waited relaxed while wearing their watch until a digital read-out indicated that the measurement was complete (approximately 30 seconds). Following the sensor reading, the app then asked the same questions regarding location, who they were with, and recent exercise, after which participants were presented with a rotating set of questions that repeated at set intervals. Note that participants could check their HR and BP at any time although our analysis only involves check-ins that included the emotion question.

As an incentive to participate, participants received immediate feedback about HR and BP. In both samples, active participants received summaries of their overall stress at the end of 21 days. In Sample B, active participants were entered into a lottery for a Samsung smartphone. Participants could continue using the app after the primary study ended after 21 days. This study was approved by the Human Research Protection Program at the University of California, San Francisco (Institutional Review Board No. 17-24159; 19-27169). Deidentified data and R codes used for this present work can be found at https://osf.io/m2qdg/.

Table 1 Sample Characteristics

	Sample A (2019 – 2021)	Sample B (2018 – 2019)
N	5,261	9,175
# of Check-ins	33,948	100,775
# of Positive/Low	21,018 (62%)	46,192 (46%)
# of Positive/High	6,151 (18%)	31,677 (31%)
# of Negative/Low	5,243 (15%)	12,133 (12%)
# of Negative/High	1,536 (5%)	10,793 (11%)
Sex		
Male	3,675 (70%)	7,063 (77%)
Female	1,559 (30%)	2,094 (23%)
Other/Unidentified	27 (< 1%)	18 (< 1%)
Age *M* (*SD*)	48.44 (12.94)	39.85 (12.43)
18 – 29	358 (7%)	2,017 (22%)
30 – 39	966 (18%)	2,827 (31%)
40 – 49	1,520 (29%)	2,374 (26%)
50 – 59	1,317 (25%)	1,263 (14%)
60 – 69	786 (15%)	548 (6%)
70+	314 (6%)	146 (2%)
Race[a]		
White	3,941 (75%)	6,616 (72%)
Asian/Pacific Islander	494 (9%)	1,178 (13%)
Black	321 (6%)	647 (7%)
American Indian	117 (2%)	113 (1%)
Other/Unidentified	593 (11%)	929 (10%)
Ethnicity		—
Latinx	466 (9%)	
Country		—
United States	3,611 (67%)	
United Kingdom	486 (9%)	
Australia	433 (8%)	
Canada	315 (6%)	
India	91 (2%)	
Singapore	85 (2%)	
Hong Kong	39 (1%)	
New Zealand	28 (1%)	
Other/Unidentified	173 (3%)	
Hypertension		—
Yes	1,737 (33%)	
Heart disease		
Yes	370 (7%)	

[a]Multiple responses were allowed. The exact wording of options for race was as follows: White/European, Asian, Pacific Islander, Black or African-American, American Indian or Alaska Native in Sample A, and Caucasian, Asian/Pacific Islander, African American, Native American in Sample B

Measures

Emotion Grid At each relevant afternoon check-in (i.e., every third day for Sample A and every day for Sample B), participants were asked how they were feeling and were presented with the following four options, depicted as four quadrants (see Fig. 1): positive & low activated (such as calm, relaxed, content, happy, sleepy, loved), positive & high activated (such as energized, alert, inspired, happy, proud, excited), negative & low activated (such as bored, tired, sad, depressed, disengaged, checked-out), and negative & high activated (such as nervous, afraid, angry, upset, hostile, disgusted; see Russell, 1980; Russell & Barrett, 1999). In our pilot study prior to the launch of the study, we had individuals self-generate emotion/feeling words. Words associated

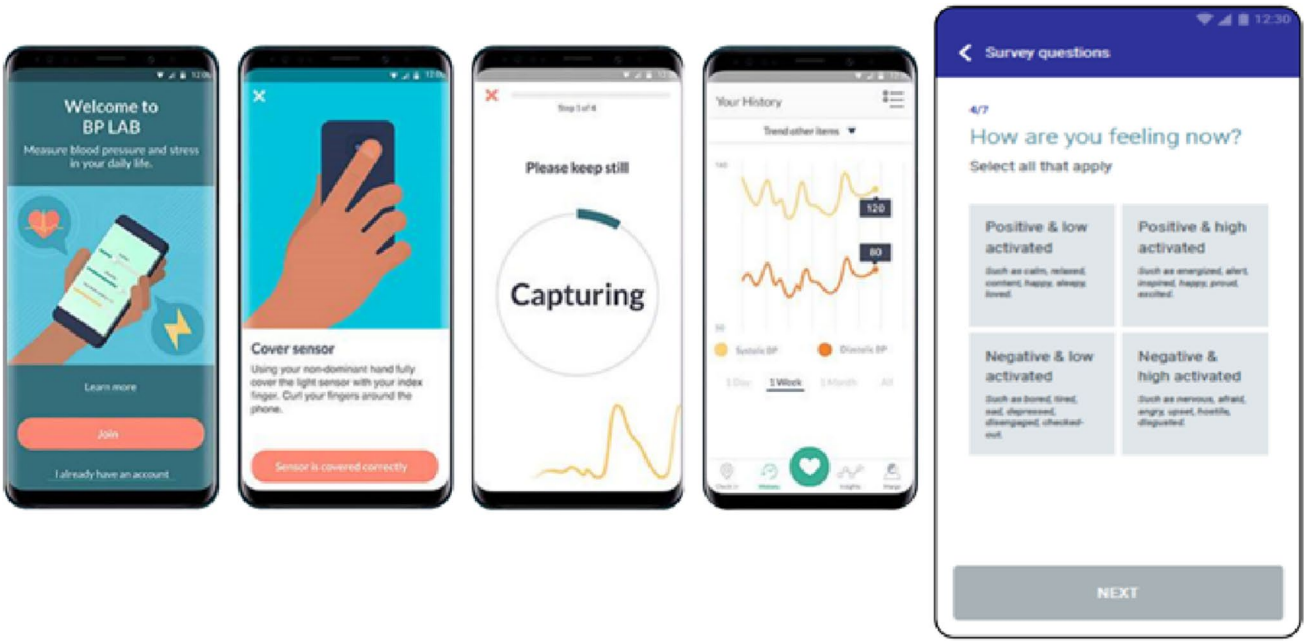

Fig. 1 Illustration of the Mobile Assessment

with typically non-emotion states like "tired" and "sleepy" were commonly provided thus were included in the grid. Of note, this grid was a much-simplified version of the affective circumplex and did not allow for assessment of the "degree" of valence or arousal. Rather, we provided participants with a range of possible emotions varying in the degree of valence and arousal that fall within each of the four quadrants and then followed up by asking how intensely they were feeling that way. As such, this emotional grid is arguably situated between the dimensional and discrete emotion perspectives. Note that in Sample A, participants were explicitly told that they could select multiple quadrants. However, as there were relatively few check-ins in which two or more quadrants were selected (< 7%) and given that simultaneous emotional experiences add complexity in addressing our research question, we focus here on check-ins with a single quadrant selected. Please see the Supplemental Materials for more details on check-ins in which participants selected multiple quadrants and analyses with full data.

Following participants' selection of a quadrant, participants indicated how intensely they were feeling the selected emotional state. Of note, this intensity variable was used by Gordon and Mendes (2021). Specifically, using a subsample from Sample B, they examined whether age moderates the link between emotional intensity and physiological reactivity, separately in each of the four emotion quadrants. They found some differences in the effects of intensity as well as its interaction with age across the quadrants, but quadrant differences were not of primary focus and thus were not tested for statistical significance. The present research, on the other hand, focuses on testing the question of whether age moderates the link between the type of emotion experienced (i.e., choice of the quadrant) and physiological reactivity. Please see the Supplemental Materials of Gordon and Mendes (2021) for the role of emotional intensity in the link between age and BP in Sample B; we also reported results of the analyses involving intensity interactions (age × valence × intensity and age × arousal × intensity) in Sample A in our Supplemental Materials.

Physiological Reactivity At every check-in, participants' HR, SBP, and diastolic BP (DBP) were estimated from an embedded optic sensor. Given the novelty of the current (and similar) cuffless methods for estimating BP (see reviews by Bard et al., 2019 and Bayoumy et al., 2021), our lab conducted validation studies, one of which included 123 participants who provided multiple BP measurements in two lab visits and in their daily lives for a week (reported in Gordon & Mendes, 2021). BP measurements were obtained simultaneously using the optic sensor, either on the phone or smart watch, and a Food and Drug Administration (FDA) approved BP cuff. In summary, we observed average correlations of $r_{sbp} = .75$, $r_{dbp} = .87$, and $r_{hr} = .98$ between phone- and cuff-based measurements and $r_{sbp} = .77$, $r_{dbp} = .83$, and $r_{hr} = .95$ between watch- and cuff-based measurements. Moreover, in a subsequent study, we compared two FDA-approved BP cuff monitors to each other using the same protocol and found similar correlations: $r_{sbp} = .75$, $r_{dbp} = .72$, and $r_{hr} = .90$. These data demonstrate that BP, in general, has more error in its estimation than HR, which is a relatively easy measure

to obtain. However, the optic sensor provided reasonable estimates of BP and performed as well as cuff-based monitors approved by the FDA. The full description and results of the validation study are available in Gordon and Mendes (2021) and Mak et al. (2023).

Upon joining the current study, participants were encouraged to calibrate the sensor to optimize the accuracy of the BP measures. Specifically, participants were encouraged to use an FDA-regulated cuff with a Bluetooth-enabled sensor, which allowed the BP values to directly populate the app with the SBP and DBP values. Once the BP values were registered by the app, participants placed their finger over the optic sensor, and the sensor used the calibration values in the algorithm to estimate sensor BP data. Note that if participants did not have a Bluetooth-enabled BP monitor, they could also manually enter their values from a doctor's visit or from another BP monitor. The app instructed participants to obtain a "gold standard" measurement of BP for optimal accuracy. We also encouraged participants to recalibrate if needed—if participants calibrated with an at-home BP monitor but then went to the doctor's office, they could update their calibrated BP data. The app did not display BP levels unless there were calibration values provided (only percent changes were shown).

In using the calibration values to adjust the raw sensor estimates, we first calculated offset values (i.e., the difference between each calibration value and a fixed default calibration value [SBP = 125 and DBP = 64]). Then, we subtracted these offset values from the raw sensor estimates. This way, we accounted for the variability in potentially multiple calibration values a given participant provided. For participants who never calibrated their data, the default calibration values (thus offset value of 0) were used.

Next, to derive reactivity scores, our primary outcome variables, we subtracted "baseline" levels of SBP and DBP from these adjusted values (and for HR, baseline levels of HR from raw sensor estimates). We considered HR and BP at a check-in with the lowest HR value as the proxy for the "baseline" for each participant (see Gordon & Mendes, 2021, for a similar approach). As previously noted, this baseline is not identical to that used in laboratory studies in which participants' resting state (e.g., prior to emotion induction) is considered, but we used it as a proxy given that resting HR is, by definition, the number of times the heart beats while a person is not engaging in any activity or stress, typically corresponding to the lowest value a given person would experience on a regular basis.

Data Exclusion and Cleaning

Given our focus on the within-person associations, we analyzed individuals with three or more check-ins with emotion reports (DiGiovanni et al., 2021; Newman et al., 2022). We excluded individuals with missing data on age or with Body Mass Index (BMI) < 15 or > 60. We also excluded check-ins in which extreme values of HR (< 30 and > 200), SBP (< 80 and > 210), or DBP (< 50 and > 180) were recorded (either in raw sensor estimates or when calibrated). Finally, we excluded check-ins if participants indicated having exercised vigorously within the past 30 min as it can temporarily increase HR and BP.

Analytic Plan

Preliminary Analyses We first examined whether age is associated with the frequency of reporting each type of emotion (i.e., positive or negative, and high or low arousal). Four separate logistic regression models were run to predict the proportion of check-ins in which a person reported a given emotion over their total number of check-ins in which they reported any emotions. Overdispersion was accounted for by refitting a quasi-binomial model.

Primary Analyses All analyses predicting BP and HR reactivity were conducted in R using the *lme4* package (Bates et al., 2015). We fitted multilevel models in which check-ins were nested within individuals. We created and included in the model two dummy variables denoting the valence (positive = 0; negative = 1) and arousal (low = 0; high = 1) of the selected emotion quadrant at each check-in. Given our primary interest in influences of age, we included its interaction with both valence and arousal. Both emotion dummies (i.e., Level-1 variables) were person-mean centered and their person means as well as age (i.e., Level-2 variables) were grand-mean centered. We allowed both the intercept and slopes of valence and arousal to vary across participants. Note that we also explored the possibility of an interaction between valence and arousal, but no significant effects were found. A sample model equation is presented below.

$$\begin{aligned} Outcome_{ij} = {} & \gamma_{00} + \gamma_{01}(Age_j) + \gamma_{02}(Valence.Mean_j) + \gamma_{03}(Arousal.Mean_j) \\ & + \gamma_{04}(Valence.Mean_j)(Age_j) + \gamma_{05}(Arousal.Mean_j)(Age_j) \\ & + \gamma_{10}(Valence_{ij}) + \gamma_{20}(Arousal_{ij}) + \gamma_{11}(Valence_{ij})(Age_j) \\ & + \gamma_{21}(Arousal_{ij})(Age_j) + u_{0j} + u_{1j}(Valence_{ij}) + u_{2j}(Arousal_{ij}) + r_{ij} \end{aligned}$$

We started with a maximal model, specifying all Level-1 predictors as random slopes, to adequately control for Type 1 error. However, given the complexity of such models (Barr, 2013; Volpert-Esmond et al., 2021), we had to simplify our model in cases where we encountered singular fit warnings. We have noted such changes in model descriptions. All models also controlled for sex (male/female/other) and grand-mean centered BMI.

Additional Analyses Finally, we examined whether sex, race, and in Sample A, country, year of the data collection

(2019 vs. 2020/2021, to account for the potential influence of the COVID-19 pandemic), and having medical conditions (hypertension, heart disease) moderate the effects of interest.

Robustness Check Given the various ways in which our data processing could have affected the results, we performed a multiverse analysis (Steegen et al., 2016), considering five different decisions: (a) sample inclusion criteria: having a minimum of three, four, five, or six check-ins, (b) sample exclusion criteria: excluding super-responders (people with more than 100 check-ins) or not, (c) check-in exclusion criteria: excluding check-ins after the 100th check-in or not [only applicable when super-responders were included in b], (d) check-in exclusion criteria: excluding check-ins where participants reported 0 (not at all) intensity for the selected emotion or not, and (e) covariates: including sex and BMI only, race added, country added, year of data collection added, or medical conditions (hypertension, heart disease) added to sex and BMI. The number of minimum check-ins was kept as three in Sample A given that reducing the sample size resulted in convergence problems; no covariates other than race could be added in addition to sex and BMI in Sample B as we did not have information on other covariates. This resulted in a total of 30 and 48 combinations (i.e., "universes") in Samples A and B, respectively. We examined how the three key effects of interest (the main effect of age and interaction effects between age and valence, and between age and arousal) are affected by these decisions.

Inference Criteria Considering the large sample size of our datasets (also see Weston et al., 2019) and multiple hypothesis testing (three outcomes for all models), we adopted a conservative alpha level ($p < .01$) for inferring statistical significance.

Results

Preliminary Results

On average, people reported feeling positive (high or low arousal) 80% of the time they reported their emotion in Sample A and 76% of the time in Sample B. More specifically, the average likelihood of a person reporting low-arousal positive, high-arousal positive, low-arousal negative, and high-arousal negative were 62%, 18%, 15%, and 5% in Sample A and 47%, 29%, 12%, and 13% in Sample B.

Figure 2 presents the proportion of each emotion experience, separated by age groups (categorized only for illustrative purposes; age was kept continuous in all analyses). In both samples, the most commonly experienced emotional state in daily life across age groups was low-arousal positive emotion, and the least experienced emotion was high-arousal negative emotion. Additionally and consistent with previous research (English & Carstensen, 2014), the proportion of positive emotions (high and low arousal combined) was higher in the older (vs. younger) age groups. Results from regression models confirmed that age was associated with a greater likelihood of reporting positive emotions, high or low arousal, in both samples (Sample A: $zs > 3.72$, $ps < .001$; Sample B: $zs > 8.46$, $ps < .001$). Age was also associated with less likelihood of reporting negative emotions, high or low arousal (Sample A: $zs < -8.53$, $ps < .001$; Sample B: $zs < -16.99$, $ps < .001$).

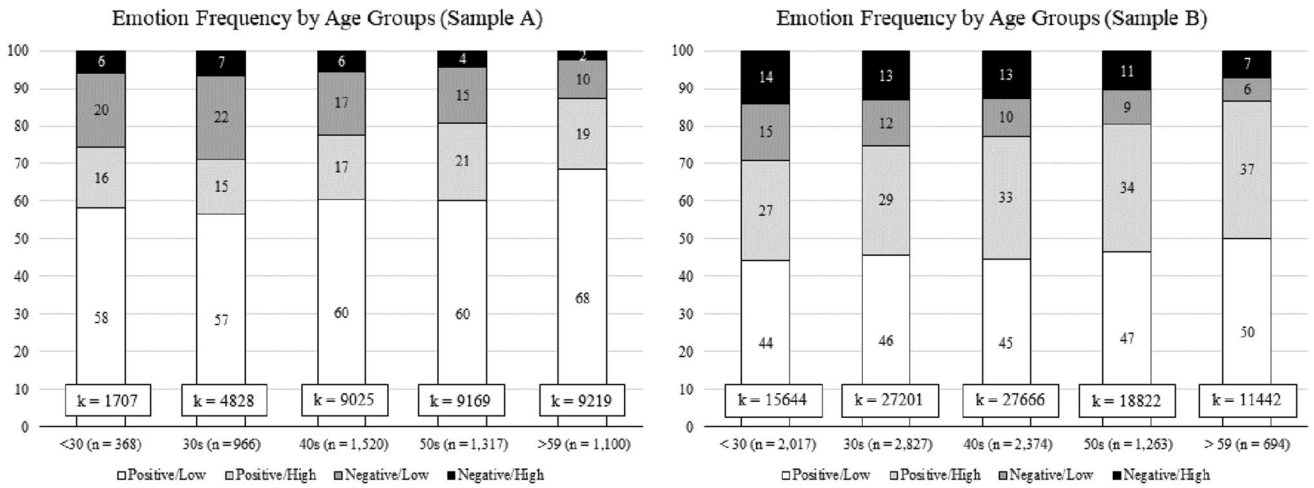

Fig. 2 Emotion Frequency by Age Groups. *Note*. The proportion of a given type of emotion reports over the total number of reports (*k*) in each age group (consisting of *n* individuals) is presented

Primary Results

Sample A

We then examined our primary questions regarding how age, valence and arousal of emotions interactively relate to physiology. As expected, we observed significant main effects of age across the three models, such that older individuals showed lower HR, SBP, and DBP reactivity (Table 2; also see the Supplemental Materials for the main effect of age on reactivity per quadrant). We also observed significant main effects of valence and arousal, such that individuals showed greater HR, SBP, and DBP reactivity when experiencing negative (vs. positive) emotions, or high (vs. low) arousal emotions. Finally, there was a significant interaction between age and arousal with SBP as an outcome. As illustrated in Fig. 3, older individuals showed lower SBP reactivity compared to younger individuals, but this age difference was larger when participants were experiencing high arousal emotion, b=-.04, $t(7776)$=-5.37, p<.001, compared to low arousal emotions, b=-.02, $t(7777)$=-3.18, p=.001. Note, however, the two total R^2 measures we reported to help interpret the importance of our predictors in predicting physiologic outcomes. While our models as a whole accounted for 19% to 45% of the total outcome variance, this was hardly attributable to our predictors (via fixed or random effects); rather, a large amount of variance was explained by the heterogeneity across individuals (random intercept variation), a point we revisit in the discussion.

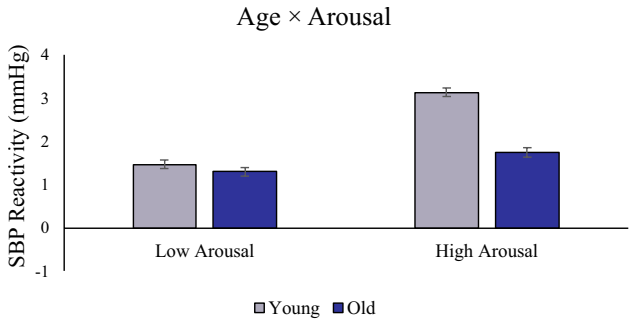

Fig. 3 Age Differences in SBP Reactivity to High vs. Low Arousal Emotional Experiences (Sample A). *Note*. Old and young represent one standard deviation above and below the mean levels of age. Error bars indicate standard errors. Reactivity was calculated by subtracting participants' baseline levels of HR and BP (levels at a check-in with the lowest HR) from the respective responses at the time of emotion reports

Sample B

Table 3 shows that all the main effects found in Sample A were replicated in Sample B. Again, age was associated with lower physiological reactivity (across quadrants; see the Materials). Moreover, experiences of negative (vs. positive) and high (vs. low) arousal emotions were independently associated with greater physiological reactivity. However, we found evidence for both age×valence and age×arousal interactions in all three models in this larger sample. First, we found that age differences in HR, SBP, and DBP reactivity were larger when participants reported high (vs. low) arousal emotions. Specifically, older vs. younger individuals' differences in physiologic reactivity were larger when participants reported high arousal emotions (b_{hr}=-.05, t[8972]=-8.67, p<.001, b_{sbp}=-.09, t[9689]=-16.98, p<.001, and b_{dbp}=-.05, t[9801]=-11.90, p<.001) than low arousal emotions (b_{hr}=-.03, t[9402]=-5.07, p<.001, b_{sbp}=-.07, t[9695]=-14.16, p<.001, and b_{dbp}=-.05, t[9777]=-10.07, p<.001). These differences are illustrated in the left side of Fig. 4 (i.e., the gap between grey and purple bars is larger for high arousal emotions).

Table 2 Summary of Results from Multilevel Models (Sample A)

	HR Reactivity				SBP Reactivity[a]				DBP Reactivity[a]			
	b	*t*	*p*	99% CI	*b*	*t*	*p*	99% CI	*b*	*t*	*p*	99% CI
Age	-.03	-5.44	<.001	[-.05, -.02]	-.03	-4.67	<.001	[-.05, -.01]	-.02	-3.07	.002	[-.03, -.00]
Valence	.30	1.76	.078	[-.14, .73]	.91	6.64	<.001	[.55, 1.26]	.64	6.48	<.001	[.39, .90]
Arousal	1.25	8.43	<.001	[.87, 1.63]	.53	4.92	<.001	[.25, .81]	.09	1.13	.258	[-.11, .28]
Age×Valence	-.02	-1.32	.187	[-.05, .02]	.02	1.45	.146	[-.02, .04]	.01	1.23	.220	[-.01, .03]
Age×Arousal	-.02	-1.62	.105	[-.05, .01]	-.03	-2.78	.006	[-.05, -.00]	-.01	-2.00	.045	[-.03, .00]
$R_t^{2(fvm)}$	.19				.40				.45			
$R_t^{2(fv)}$	.02				.01				.01			

HR=Heart rate; SBP=Systolic blood pressure; DBP=Diastolic blood pressure. [a]Models without a random slope of arousal. Reactivity was calculated by subtracting participants' baseline levels of HR and BP (levels at a check-in with the lowest HR) from the respective responses at the time of emotion reports. All models also included person means of valence and arousal, sex, and BMI. Valence was coded as 0=positive, 1=negative; Arousal was coded as 0=low, 1=high. $R_t^{2(fvm)}$= Proportion of total outcome variance explained by predictors via fixed slopes and random slope (co)variation and by person-specific outcome means via random intercept variation. $R_t^{2(fv)}$= Proportion of total outcome variance explained by the Level 2 predictors via fixed slopes and random slope (co)variation only (Rights & Sterba, 2019)

Table 3 Summary of Results from Multilevel Models (Sample B)

	HR Reactivity				SBP Reactivity				DBP Reactivity			
	b	*t*	*p*	99% CI	*b*	*t*	*p*	99% CI	*b*	*t*	*p*	99% CI
Age	-.04	-7.88	< .001	[-.05, -.03]	-.08	-16.55	< .001	[-.09, -.07]	-.05	-11.59	< .001	[-.06, -.04]
Valence	.34	3.48	< .001	[.09, .59]	1.19	18.46	< .001	[1.03, 1.36]	.99	18.17	< .001	[.85, 1.13]
Arousal	1.31	16.16	< .001	[1.10, 1.51]	.90	17.18	< .001	[.76, 1.03]	.45	10.05	< .001	[.33, .56]
Age × Valence	-.02	-2.78	.005	[-.04, -.00]	.02	4.66	< .001	[.01, .04]	.03	6.99	< .001	[.02. .04]
Age × Arousal	-.03	-4.22	< .001	[-.04, -.01]	-.02	-5.09	< .001	[-.03, -.01]	-.01	-3.22	< .001	[-.02, -.00]
$R_t^{2(fvm)}$	.23				.45				.48			
$R_t^{2(fv)}$	.3				.04				.03			

HR = Heart rate; SBP = Systolic blood pressure; DBP = Diastolic blood pressure. Reactivity was calculated by subtracting participants' baseline levels of HR and BP (levels at a check-in with the lowest HR) from the respective responses at the time of emotion reports. All models also included person means of valence and arousal, sex, and BMI. Valence was coded as 0 = positive, 1 = negative; Arousal was coded as 0 = low, 1 = high. $R_t^{2(fvm)}$ = Proportion of total outcome variance explained by predictors via fixed slopes and random slope (co)variation and by person-specific outcome means via random intercept variation. $R_t^{2(fv)}$ = Proportion of total outcome variance explained by the Level 2 predictors via fixed slopes and random slope (co)variation only (Rights & Sterba, 2019)

Next, we probed the interactions between age and valence, which suggested different patterns of results for HR and BP reactivity. As illustrated by the gap between the grey and purple bar on the right side of Fig. 4, age differences in HR reactivity were larger when participants reported experiencing negative emotions than positive emotions ($b_{negative}$ = -.04, t[8466] = -8.18, p < .001, and $b_{positive}$ = -.03, t[9179] = -5.56, p < .001). However, age differences in SBP and DBP reactivity were larger when participants reported experiencing positive emotions (b_{sbp} = -.09, t[9650] = -17.09, p < .001 and b_{dbp} = -.06, t[9696] = -13.13, p < .001) than negative emotions (b_{sbp} = -.07, t[9468] = -13.88, p < .001, and b_{dbp} = -.04, t[9682] = -8.71, p < .001). As in Sample A, however, we note that only a small amount of the total variance was explained by our predictors.

Additional Results

Sample A Sex, race, country, or year of data collection did not moderate any of the effects.

Sample B Three significant three-way interactions are depicted in Fig. 5. The three-way interaction between sex, age, and valence was significant when predicting SBP reactivity, b = 0.04, t(3212) = 3.12, p = .002, such that the interaction between age and valence (in the direction reported in our primary analysis) was significant among females, b = 0.05, t(3200) = 5.10, p < .001, but not among males, b = 0.01, t = 2.49, p = .01 (see top panels in Fig. 5). That is, among males, age differences appeared similar whether participants reported positive or negative emotions. The interactions between race (white as the reference group), age, and arousal predicting SBP and DBP reactivity were also significant when white vs. black was concerned (b_{sbp} = .06, t[3303] = 2.95, p = .003, and b_{dbp} = .05, t[3800] = 3.02, p = .003). Specifically, as illustrated in Fig. 5 (SBP reactivity in the middle and DBP reactivity at the bottom), the interaction between age and arousal was significant among White people (b_{sbp} = -.03, t[3413] = -6.29, p < .001, and b_{dbp} = -.02, t[3940] = -4.35, p < .001) but not among Black people (b_{sbp} = .03, t[3296] = 1.46, p = .15, and b_{dbp} = .03, t[3791] = 2.02, p = .04). That is, age differences in BP reactivity did not differ across high and low arousal emotions for Black people.

Multiverse Analyses

Table 4 shows that our primary results generally held across different "universes" although the likelihood of obtaining a significant interaction between age and valence predicting HR reactivity in Sample B was lower than the chance level. Figures depicting a summary of the multiverse analysis can be found in the Supplemental Materials.

Discussion

Our analyses of the daily emotions and physiology showed greater BP reactivity associated with negative (vs. positive) or high (vs. low) arousal emotions, and greater HR reactivity associated with high (vs. low) arousal emotions. Further, as expected from the biological processes of aging (Cacioppo et al., 1998) and maturational dualism (Mendes, 2010), age was associated with lower HR and BP reactivity to emotions overall. Reduced physiologic reactivity to emotions can

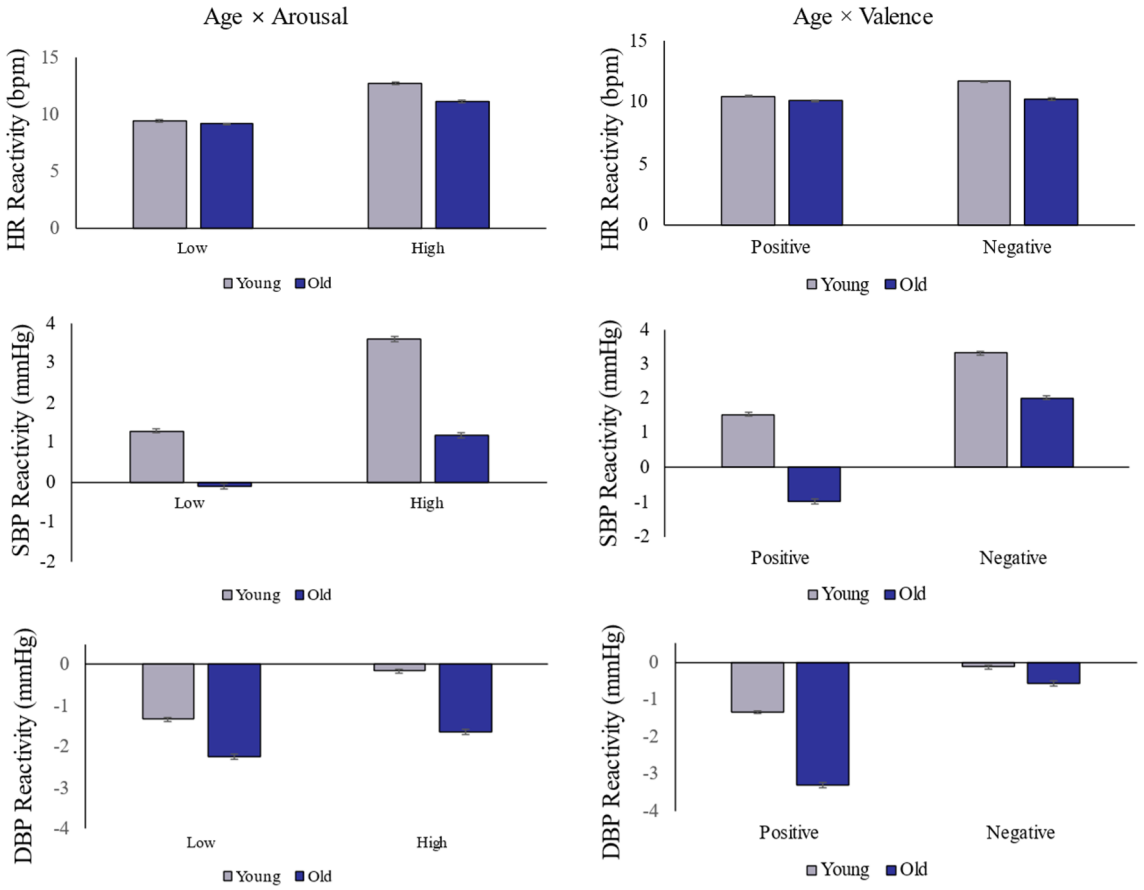

Fig. 4 Age Differences in Physiological Reactivity to Low vs. High Arousal (Left) and Positive vs. Negative (Right) Emotional Experiences (Sample B)**.** *Note*. Error bars indicate standard errors. Old and young represent one standard deviation above and below the mean levels of age. Reactivity was calculated by subtracting participants' baseline levels of HR and BP (levels at a check-in with the lowest HR) from the respective responses at the time of emotion reports

serve an adaptive function for older individuals for whom recovery from heightened physiological states takes longer (Wrzus et al., 2014), and thus, the same degree of reactivity can be more costly. This includes long-term health costs as elevated BP in daily life is related to adverse outcomes such as an increased risk of developing cardiovascular diseases (Kannel, 2000).

Further, extending previous findings on age differences in reactivity to discrete emotions (Seider et al., 2011), we showed that the type of emotions older and younger adults react differently to in daily life can be conceptualized in broader dimensions. Specifically, age differences in HR and BP reactivity appeared larger during high (vs. low) arousal emotions and those in BP reactivity larger during positive (vs. negative) emotions (in Sample B). These results complement previous findings, painting a fuller picture of age differences in physiologic responses to emotions. Especially considering mixed evidence for physiological specificity to discrete emotion categories (Kreibig, 2010; Siegel et al., 2018; Zelenski & Larsen, 2000), a broader conceptualization of the type of emotions for which age differences manifest can be informative. Using EMA to observe naturally occurring emotions was a strength in that regard, as emotion induction typically necessitates a focus on discrete emotions (despite potentially eliciting more than the targeted emotion; Stephens et al., 2023). Further, for capturing daily emotional experiences, the image-based assessment we used seems promising, with our findings generally supporting its utility and validity (e.g., the prevalence of low arousal positive emotions), despite its limitations in capturing the *degree* of arousal or valence.

Future research could explore how age modulates the dynamic time course of emotional and physiological experiences. With once-per-day assessments, we can only assume that participants were reacting to emotions at the time of assessments. However, experiences of emotions and responses to them occur continuously in life (e.g., before, during, and after a concert). Collecting data with more intensive assessment schedules can help capture anticipatory,

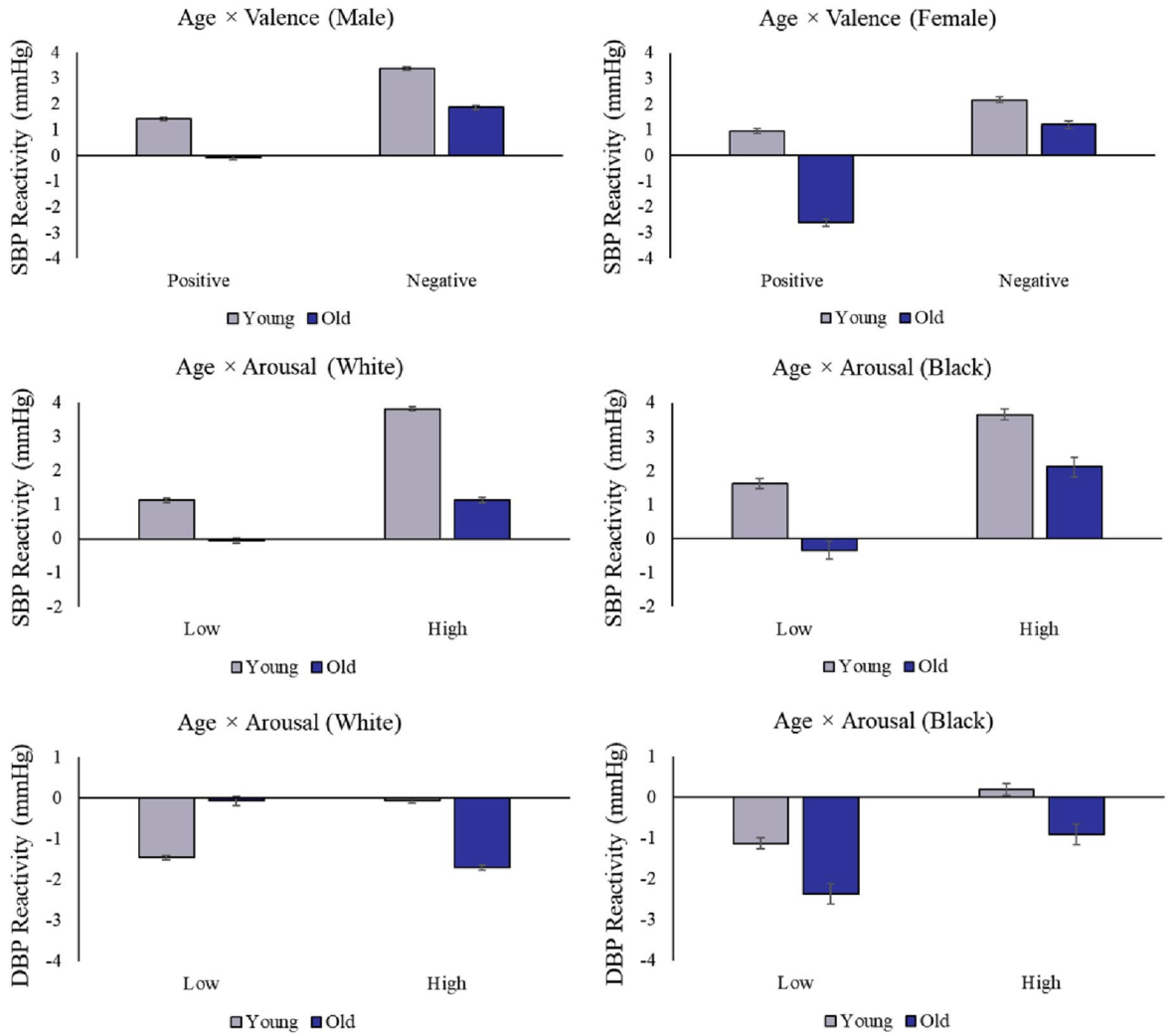

Fig. 5 Age Differences in Physiological Reactivity to Emotions of Different Kinds, Moderated by Sex and Race (Sample B). *Notes.* Error bars indicate standard errors. Old and young represent one standard deviation above and below the mean levels of age. Reactivity was calculated by subtracting participants' baseline levels of HR and BP (levels at a check-in with the lowest HR) from the respective responses at the time of emotion reports

Table 4 Results from the Multiverse Analyses

	Sample A			Sample B		
	HR	SBP	DBP	HR	SBP	DBP
Age	100%	100%	100%	100%	100%	100%
Age × Valence	0%	0%	0%	38%	100%	100%
Age × Arousal	0%	67%	0%	100%	100%	100%

The proportion of significant ($p < .01$) results is shown. A total of 30 and 48 universes were considered for Samples A and B, respectively

reactive, and recovery processes related to an emotional event and the role of age in these processes (Luong et al., 2018). Such data could also allow researchers to model the complex coupling of mind and body. Further, although we considered physiological responses to be shaped by emotional experiences, the other direction is worth considering; for example, age differences can be interpreted as reflecting differences in interoceptive ability (i.e., muted responses to bodily changes among older individuals; MacCormack et al., 2021; Mendes, 2010). For a fuller understanding of what role age plays in mind–body interaction, future research should consider the possibility of bidirectional relations.

Also noteworthy is how little our predictors explained variance in physiologic outcomes. On the one hand, in daily contexts where physiologic responses are affected by a host of moving factors (e.g., posture, noise), the small effect sizes are understandable and even highlight the strength of analyzing large samples that allowed us to observe such effects. Indeed, not much work exists that provides insight into how much of daily physiological reactivity can be explained by psychological variables. On the other hand, a great degree of heterogeneity in physiologic reactivity observed across individuals not attributable to our predictors suggests that several strengths of our research may also be its limitation. Using ambulatory assessments and large samples of participants with great variability could produce a lot of noise. The absence of a controlled baseline assessment could have further added to this noise. Yet, as with other small but practically significant effects (Götz et al., 2022), it is possible that over time, these small differences accumulate in ways that create meaningful divergences in the mental and physical health of younger and older adults. In particular, understanding age differences in affective predictors of BP reactivity holds implications for physical health as elevated BP and BP reactivity are related to increased risk of developing cardiovascular diseases (Dolan & O'Brien, 2015; Kannel, 2000).

Limitations

Our samples were relatively limited in terms of cultural diversity, partly due to the eligibility criteria that included fluency in English (almost 70% of the app downloads were from the US). Given that recruitment took place on a mobile platform and arguably targeted those interested in their health, we also cannot rule out selection bias. Further, the representativeness of the emotions captured in our assessments remains unclear (e.g., greater likelihood of skipping check-ins during high arousal negative emotional experiences). Finally, given the short data collection period, our analysis cannot distinguish age effects from cohort or period effects (Bell, 2020).

We also note meaningful differences across the two samples. For example, Sample A showed more extreme ratio differentiation in emotion categories (see Fig. 2), which may be due to 1) the change in the response format (allowing for multiple quadrant selection in Sample A vs. not in Sample B); 2) the frequency with which we asked about emotions (every third day in Sample A vs. every day in Sample B); or 3) other differences. The first possibility warrants particular attention as the possibility of different response options (mis)representing people's emotional experiences has implications for survey design and data interpretations. The second possibility is also important given that simply reporting one's emotional responses can alter physiological reactivity to the emotion (Kassam & Mendes, 2013).

Considering the long-term health consequences of physiological reactivity (e.g., Dolan & O'Brien, 2015), exploring affective predictors of daily physiological reactivity is important for understanding how emotional life and physical health are intertwined; further, studying age differences therein can inform us of how such dynamics unfold across the life span. Here, we provided ecologically valid evidence for reduced physiologic reactivity to emotions (particularly those of high arousal) among older individuals. While acknowledging the differences in the operationalization of physiologic reactivity, or perhaps especially given such differences, our findings complement and extend previous findings in the laboratory. Employing a method that closely mirrors real-life emotional experiences and responses, future research should further examine the mechanisms underlying our findings.

Additional Information

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Competing Interests The authors declare no competing interest.

Data Availability Data and Code Availability used for this work are available at https://osf.io/m2qdg/.

Code Availability Not applicable.

Author Contribution All authors contributed significantly to the conceptualization, and writing and editing of the manuscript. All authors have approved the final version of the submitted manuscript.

Ethics Approval This study was approved by the Human Research Protection Program at the University of California, San Francisco (Institutional Review Board No. 17-24159; 19-27169). Informed consent was obtained from all individual participants included in the study.

Consent to participate Not applicable.

Consent for publication Not applicable.

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