AFFECT-BIASED HEALTH PERCEPTIONS: HOW GLOBAL AND DAILY AFFECT INFLUENCE THE CORRESPONDENCE BETWEEN OBJECTIVE AND SUBJECTIVE HEALTH IN OLDER ADULTS

A Dissertation

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by

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Abstract

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Research has revealed the presence of affective bias in self-reports and self-assessments of global health, resulting in a discrepancy between individuals’ reports of their own health and those of more objective health assessments. This bias, which occurs with both negative and positive affect (NA/PA) on both trait and state levels, can be problematic in the contexts of medical treatment and academic research. The present study investigated the presence of affectively-biased health perceptions on both global and daily levels, and also explored cross-level affective bias effects. Participants were 152 older adults who completed: scales measuring global affect and perceived health; daily questionnaires for 56 days on affect, health events, and health satisfaction; and an in-person health assessment including a health interview, a physical, a blood assay, and the collection of medical records. On the global level, structural equation modeling was used to evaluate the presence of affective health bias, so that the relationship between an Objective Health factor and a Perceived Health factor is moderated by global NA and PA. On the daily level, multilevel modeling was used to test the extent to which the
impact of a given day’s health events on that day’s health satisfaction is moderated by
that day’s NA and PA. Additional models also tested the degree to which health bias is
primarily a trait process (dependent on global affect) or a state process (dependent on
day-level affect). Results revealed evidence for NA bias on the global level; PA did not
significantly moderate the association between the Objective and Perceived Health
factors, but results did suggest that PA serves to counteract NA bias to an extent. On the
daily level, both NA and PA biased day-level health perceptions individually, but only
NA maintained its moderating effect when both affective biases were tested
simultaneously. None of the cross-level effects in the day- vs. global-level affect bias
models were significant, indicating that health bias processes are largely confined within
level of measurement/analysis. These results inform future procedures of medical
professionals and academic researchers who rely on subjective health data for appropriate
treatment decisions and accurate empirical conclusions.
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CHAPTER 1

INTRODUCTION

Although medical professionals and researchers primarily rely on objective indicators of health when making treatment decisions and drawing empirical conclusions, there are many occasions when, whether due to limited time or limited resources, they must base their decisions on subjective patient reports and health ratings. It is therefore important that such subjective ratings be accurate, and as unbiased by the individual’s personality and emotional state as possible—the more unbiased they are, the more closely they should approximate the information that would be obtained through more objective health measures. The present project is designed to shed light on the extent to which affect (both state and trait in nature) predicts biased health perceptions in older adults. The primary aims guiding the investigation are: 1) to examine the influence of both positive and negative affect—comprising both high- and low-arousal affective elements—on the presence of global and daily health bias; 2) to explore the extent to which the presence of health bias on both the global and daily levels is best predicted by stable, trait-level affect characteristics or by day-level affective moods; and 3) to investigate these effects and processes within the context of a general health evaluation, rather than within a paradigm restricted to a single diagnosis (e.g., asthma) or symptom (e.g., heart rate). These aims represent novel aspects of the present project that will
contribute to the literature on affect-related health bias; the literature review to follow is organized to highlight the importance of these aims within the context of this study.

1.1 Affect-Biased Health Perceptions

Research indicates a common presence of affective bias when it comes to self-reports and self-assessments of global health, resulting in a discrepancy between individuals’ reports of their own health and those of more objective health assessments (Gijsbers van Wijk & Kolk, 1997; Powell, Johnston, & Johnston, 2008; Watson & Pennebaker, 1989). The extent of bias present in subjective health information is somewhat dependent on the nature of the data being collected—more general questions (e.g., “Overall, how would you rate your health?”) are more likely to fall prey to bias than more specific questions (e.g., “Do you have diabetes?”). The bias present for these more general judgments can be a factor of the information that a given individual is using to inform his or her response. For example, two individuals may be equally healthy by objective standards, but person A rates his or her overall health as “somewhat poor” whereas person B rates his or her overall health as “somewhat good.” Why the discrepancy? It is likely due to the different information that each individual uses when making their respective ratings—person A may rely on more negative/unhealthy cues when responding, whereas person B may invoke more positive/healthy information. Such positive and negative biases point back to the literature on mood congruency effects, in which individuals’ judgment processes are influenced by the extent to which they are in a positive or negative frame of mind (Fredrickson, 2000; Mayer, Gaschke, Braverman, & Evans, 1992; Park & Banaji, 2000). On the other hand, the differences in health ratings between these two equally healthy individuals may also reflect more stable personality
differences, in that person B is generally a more positive and optimistic person, whereas
person A tends to be more pessimistic in his or her approach to life (Smith, Wallston, &
Dwyer, 1995). The biasing effects of both trait- and state-level affect are of interest here.

Negative affect (NA) is the most studied predictor of biased health perceptions,
with higher levels of trait NA predicting inflated symptom reports and reports of self-
rated health that are lower than objective health measures would indicate (Bogaerts et al.,
2008; Bogaerts et al., 2005; Karsdorp, Kindt, Rietveld, Everaerd, & Mulder, 2007; Mora,
Halm, Leventhal, & Ceric, 2007; Strigo, Simmons, Matthews, Craig, & Paulus, 2008).
Positive affect (PA), although less studied in the context of health bias, also influences
people’s self-assessments of health on both state and trait levels (Benyamini, Idler,
Leventhal, & Leventhal, 2000; Bogaerts et al., 2005; Pettit, Kline, Gencoz, Gencoz, &
Joiner, 2001; Pressman & Cohen, 2005; Rietveld & Van Beest, 2006; Watson &
Pennebaker, 1989). When it comes to the literature on self-reported health and its
alignment with more objective health indices, there are very few studies that have
considered positive affect alongside negative affect, and when they do, the positive and
negative affective dimensions measured tend to be those at the high-arousal end of the
spectrum (Watson, 1988; Weisenberg, Raz, & Hener, 1998) or at different state or trait
levels (Bogaerts et al., 2005; Bogaerts et al., 2008). There is a relative dearth of research
informing a more comprehensive consideration of the range of affective experience in
relation to subjective and objective health measures, a reality that represents a divide
between theory and measurement. Most theoretical models of affect describe the affective
space in terms of both valence (positive/negative, pleasant/unpleasant,
approach/avoidance) and arousal (activated/deactivated, aroused/unaroused), meaning
that much of the affective space is often ignored in the health bias literature, which tends to focus on the effects of high-arousal negative affect (Feldman, 1995; Feldman Barrett & Russell, 1998; Thayer, 1978; Watson, Wiese, Vaidya, & Tellegen, 1999; Yik, Russell, & Feldman Barrett, 1999).

Because, as mentioned previously, many medical professionals and academic researchers rely on ratings of self-rated health and self-reported symptoms to provide them with valid information about the physical state of the individual, these affect-biased health perceptions are important to investigate. If the accuracy of information depends on the individual’s trait affect tendency and/or their current affective mood state, the conclusions and treatment decisions made may be inaccurate or less effective if these factors are not taken into account. Thus, if the influences of trait and state affect on bias in self-rated health are more fully understood, it is possible to control for these effects by, for example, cueing the preferred state of mind or phrasing questions in such a way as to avoid affective bias. The overarching goal of the present project is therefore to explore the moderating effects of both trait and state affect—conceptualized as comprising positive and negative emotions of varying arousal—on the link between objective health indicators and subjective health perceptions, both globally and on the daily level.

1.2 Conceptualizing Affect

1.2.1 Models of Affect

Several models of affect have informed and directed the literature on affective experience, but the two most relevant to how affect is measured and conceptualized in the present project are the PA/NA model (Watson, 1988; Watson et al., 1999) and the
Circumplex Model of Affect (Feldman, 1995; Feldman Barrett & Russell, 1998; Russell, 1980; Yik et al., 1999; Yik, Russell, & Steiger, 2011). Although these two models are conceptually different in terms of which components of affect comprise the primary dimensions of the affective structure, both acknowledge the presence and potential import of both low- and high-arousal affective experiences. Additionally, they theoretically justify the conceptualization of positive and negative affect as representing both activated (e.g., angry, excited) and non-activated (e.g., fatigued, relaxed) emotions in the current project; each model—and how they relate with one another—is discussed briefly below.

The *Circumplex Model of Affect* (Feldman Barrett & Russell, 1998; Russell, 1980) represents the complete range of affective experience with a circle, divided into four quadrants by two axes, or dimensions: valence (pleasant/unpleasant), and arousal (activation/deactivation). All experienced emotions fall at some point along the circumference of the circle, depending on the valence/arousal qualities of each—terms falling at the poles of the arousal dimension are devoid of valence (e.g., aroused, sleepy), high and low pleasantness terms lack an implied arousal level (e.g., happy, sad), and terms falling within the four resulting quadrants correspond to a) high-arousal pleasant moods (e.g., elated), b) high-arousal unpleasant moods (e.g., distressed), c) low-arousal pleasant moods (e.g., relaxed), or d) low-arousal unpleasant moods (e.g., depressed). This model is conceptually attractive, and empirical studies have demonstrated that affective descriptors map on to the circumplex model quite well (Feldman Barrett & Russell, 1998; Yik et al., 1999; Yik et al., 2011). The reality is, however, that there is a limited number of terms available to capture non-valenced affective states in the English language, whereas the vocabulary available to assess positive and negative affective experience is
substantially more developed. This makes it difficult to assess the entire affective space, and results in the more salient clusters of terms—specifically those at the high-arousal ends of positive and negative affective experience—explaining a more substantial portion of the variance in overall affect than lower-arousal items (Watson & Tellegen, 1985; Watson et al., 1999). These issues prompted Watson and colleagues to rotate the two-dimensional structure of affect 45 degrees, so that positive and negative affect—which comprised the quadrants, or secondary axes, of the Russell model—became the primary dimensions representing the affective space (Watson & Tellegen, 1985). In this orientation, the negative affect dimension is anchored by high negative affect (e.g., distressed, fearful) and low negative affect (e.g., calm, relaxed), whereas the poles of the positive affect dimension are high positive affect (e.g., active, elated) and low positive affect (e.g., drowsy, sluggish). Indeed, factor analyses on self-reported affect items demonstrate that positive and negative affect consistently emerge as the primary factors describing the affective space (De Bolle, De Fruyt, & Decuyper, 2010; Watson & Tellegen, 1985; Whitehead & Bergeman, 2012).

It could be argued that the PA/NA conceptualization of Watson and colleagues (e.g., 1999) is one of the most well-known theories of affect, perhaps in part due to the widespread utilization of the corresponding measure—the Positive and Negative Affect Schedule, also known as the PANAS (Watson, Clark, & Tellegen, 1988)—by social science researchers in countless empirical studies. In this model, the components of affect—Positive Affect (PA), which reflects pleasurable engagement with one’s environment, and Negative Affect (NA), which is a general factor of subjective distress—are conceptualized as independent of one another, as opposed to representing opposite
ends of a single bipolar dimension (Watson, 1988; Watson & Tellegen, 1985; Watson et al., 1999). It is important to note that the vast majority of the items used to capture the domains of positive and negative affect in the PANAS correspond to the high-activation pole of each (e.g., angry, upset, excited), whereas low-arousal (or disengagement) regions of the affective space are largely ignored (Watson et al., 1988). According to Watson and colleagues, this was done because a) high-arousal experiences are more representative of experienced emotions, b) valence dimensions are more easily and reliably measured than arousal dimensions, and c) a valence conceptualization better aligns with a personality/trait orientation—and is thereby more useful in explaining individual differences—whereas arousal may be more situational in nature (Watson et al., 1999). So, although they acknowledge the presence and potential utility of lower-arousal affective experiences under certain circumstances (Watson et al., 1999), proponents of the PA/NA model place greater import on high-arousal components of affect.

Its demonstrated validity and reliability in assessing activated positive and negative affect makes the PANAS measure a solid foundation for the operationalization of PA and NA in the present study. But because a) both trait and state affective processes are of interest in the present project, b) lower-arousal dimensions tend to be more salient at the state or daily level, and c) research has indicated that older adults are more likely to endorse lower-arousal affect—perhaps indicating its greater importance to the age group of interest here (as discussed in greater detail in the section on age effects below)—the positive and negative affect dimensions to be used here will represent a larger portion of the affect circumplex. More specifically, affect measures will include positively- and negatively-valenced items intended to capture a broader range of arousal than the original
PANAS measure, so that NA, as conceptualized here, is represented by high-arousal negative affect terms (e.g., distressed, afraid), moderate-arousal negative affect terms (e.g., miserable, worried), and low-arousal negative affect terms (e.g., depressed, fatigued); whereas PA is represented by high-arousal positive affect terms (e.g., active, enthusiastic), moderate-arousal positive affect terms (e.g., cheerful, interested), and low-arousal positive affect terms (e.g., relaxed, satisfied). These scales align somewhat with the NA and PA “superclusters” identified by Watson et al. (1999), in which the majority of affect items fall within one of two 100-degree portions of the circumplex that are approximately opposite one another, corresponding to the broad PA/pleasure and NA/unpleasant sections of the circle. This expanded conceptualization of affect satisfies Aim 1 of the current study—that affective bias be investigated within the context of both positive and negative affect, with those constructs representative of a broad range of activation.

1.2.2 State vs. Trait Affect

Affect has often been conceptualized as a trait variable, implying that there are stable individual differences in affective experience that generalize across time and contexts, and can therefore be predictive of other global, between-person constructs and outcomes (Eaton, 2004; Feldman, 1995; Watson, 1988). Countless studies have associated trait affect features with personality (Costa & McCrae, 1980; Eaton, 2004; Kessler & Staudinger, 2009), behavioral tendencies (Fredrickson, 2000; Watson et al., 1999), stress reactions and coping (Ashby, Isen, & Turken, 1999; Dowd, Zautra, & Hogan, 2010; Fredrickson, 2000), and indicators of both mental health (Fredrickson, 2000; Watson et al., 1995) and physical health (Ashby et al., 1999; Davidson, Mostofsky,
& Whang, 2010; Dowd et al., 2010; Pettit et al., 2001; Pressman & Cohen, 2005; Steptoe, Dockray, & Wardle, 2006). In a behavioral genetics study, Baker, Cesa, Gatz, and Mellins (1992) found that family similarities in trait NA tend to be genetic in origin, whereas those in trait PA tended to be environmentally based. They went on to suggest that their findings may indicate that the experience of PA is primarily situational, whereas the experience of NA is more dispositional, an idea that aligns to an extent with experimental findings, in which state PA moderates—or buffers—the biasing effect of trait NA on health perceptions (Bogaerts et al., 2005).

Within-subjects studies using daily and momentary affective experience measures have established that there is considerable variability in emotional experience within people, whether over the course of a day, a week, a month, or in the context of an experimental manipulation (Diener & Larsen, 1984; Watson, 1988; Wilt, Funkhouser, & Revelle, 2011). This variability has led a number of researchers to consider whether and how momentary or daily affect is different from global/trait affect, and what differential processes may underlie these effects. For example, a review paper on the link between positive affect and health concluded that findings in the existing literature indicate that, in the context of health and physical well-being, trait PA is more likely to have an impact over the long-term, such as chronic morbidity or mortality risk, whereas state PA tends to influence the progression of an existing disease, or the occurrence and management of acute attacks/episodes of a chronic disease (Pressman & Cohen, 2005).

Research has also identified differential physiological correlates of trait and state PA in the context of stress, indicating that these divergent underlying processes may result in different functions; specifically, there is evidence that trait PA, through the
cognitive flexibility and coping skills it promotes, aids recovery from acute stressors, whereas state PA, via its associated dopamine release, serves to counteract or “undo” the effects of NA associated with stress (Ashby et al., 1999; Papousek et al., 2010). This “undoing” role of PA aligns with Fredrickson’s Broader and Build Theory of Positive Emotions, which suggests that specific positive emotions—such as joy, interest, and love—serve to build resources that are later used to buffer or “undo” the deleterious impact of negative emotions (Fredrickson, 1998). The beneficial influence of positive emotions in the context of negative affect and health has also been supported empirically (Pressman & Cohen, 2005; Steptoe et al., 2006; Steptoe, Wardle, & Marmot, 2005).

Considering the processes and consequences of short- vs. long-term negative affect, researchers have begun differentiating between “acute” negative emotions (e.g., anger), “episodic” negative moods (e.g., depression, exhaustion), and “chronic” negative characteristics (e.g., hostility, trait NA) in order to investigate how duration impacts the effects of negative affect on mental and physical health (Smith & Ruiz, 2002). For example, in the case of risk for and development of coronary heart disease (CHD), acute negative affect increases heart rate, blood pressure, coronary constriction, inflammation, and lipid levels, while lowering plasma volume; this then contributes to short-term instability and increased demand in cardiac function (Smith & Ruiz, 2002). If intense enough, these symptoms could result in arrhythmia, ischemia, or plaque rupture, which may lead to myocardial infarction or even death. Episodic negative affect, which is less activated and more long term in nature, eventually leads to more enduring physiological symptoms such as neurohormonal changes, sympatho/vagal imbalance, and chronically-elevated lipids; these can also increase physiological susceptibility to acute negative
affect, thereby heightening the risk for and progression of CHD. Finally, trait-level negative affect does not impact physiological processes or the development of CHD directly; rather, it does so indirectly by increasing one’s vulnerability to episodic and acute negative affect and their subsequent effects (Smith & Ruiz, 2002).

In terms of function, state negative affect is thought to signal an immediate threat to one’s welfare, and is thus considered adaptive in short doses for those in otherwise good health (Cocioppo, Gardner, & Berntson, 1999; Park & Banaji, 2000). One study, for example, found that negative affect associated with acute stressors led to an increase in natural immunity functions, although other specific immunity functions were temporarily reduced (Segerstrom & Miller, 2004). Research on judgment and perception has also found that state negative affect helps to increase focus and reduce reliance on heuristic processing and stereotypes in making judgments (Forgas, 1995; Park & Banaji, 2000). If, however, the threat (and its corresponding negative affect) does not subside within a relatively short period—causing physical and psychological arousal to be maintained over a longer period of time—then the negative affect becomes maladaptive, potentially resulting in declines in the quality and functioning of physical, psychological, and emotional processes (Fredrickson, 2000; Kiecolt-Glaser, McGuire, Robles, & Glaser, 2002; Segerstrom & Miller, 2004). Long-term effects on health and well-being are thus more likely to be linked to affect measured on the global level, which taps trait-level affect processes. State or day-level affective experiences may serve as catalysts, setting these longer-term affective processes in motion or accelerating their pace; they may also provide an index of global-level affective–health processes on a more micro level.
Taken together, the literature indicates that the processes involved in and the
effects of positive and negative affect differ depending on the level of analysis; Aim 2 of
the present project will investigate affect-related health biases on both global and daily
levels, and will also explore the relationships among affects across levels to determine
how they impact objective health measures and health perceptions in older adults.

1.3 Health Bias Overview

A number of studies have compared objective health reports from physicians or
medical records with self-reported health data collected directly from participants, and
because they focus on specific diagnoses or medical procedures, they have reported fairly
high agreement rates (Bergmann, Byers, Freeman, & Mokdad, 1998; Haapanen,
Miilunpalo, Pasanen, Oja, & Vuori, 1997). Inaccuracy that exists in these specific
contexts is likely due to lack of knowledge or information, memory issues, or
overgeneralization (e.g., an individual confusing his or her malady with a diagnosis
associated with a body part or anatomical function similar to—or in close proximity to—
that affected by their own disease), rather than to biased perceptions (Bergmann et al.,
1998; Jordan, Price, King, Masyk, & Bedell, 1999; Nilsson, Johansson, Karlsson, &
McClearn, 2002). Research indicates that inaccuracy resulting from affective bias—the
focus of the current project—is present when symptoms are short-term, sporadic, and/or
have not been labeled with a specific diagnosis, or in the case of overall ratings of general
health. In these non-specific cases, agreement between objective health indicators and
subjective reports decreases considerably, and affective and perceptual biases are more
likely to come into play (Haapanen et al., 1997; Kehoe, Wu, Leske, & Chylack, 1994).
Even when an individual has received a diagnosis, such as diabetes, heart disease, or
asthma, researchers have identified considerable over- and under-reporting of symptoms when compared with objective measures of glucose, heart function, or lung function (Karsdorp et al., 2007; Mailloux & Brener, 2002; Schandry, Leopold, & Vogt, 1996). Although these people are likely very accurate in self-reporting their diagnosis, there is psychological or personal bias present when it comes to reports of physical sensations and broad self-assessments of health.

In the medical arena, the discrepancies arising from affective bias—whether reflecting under-reporting or over-reporting of symptoms—can lead to problems in terms of treatment and diagnosis, and are thereby detrimental to long-term health outcomes (Main, Moss-Morris, Booth, Kaptein, & Kolbe, 2003). The extent to which these effects are consistent, however—demonstrating stability across time, contexts, and health scenarios, and consistently influencing lifestyle and reporting behavior in the same way—depends on whether they stem from trait affect characteristics or situational mood states. Because there is evidence for substantial within-person variability for both positive and negative affect across days (Diener & Larsen, 1984; Jackson & Bergeman, 2011; Wilt et al., 2011), it is possible that affective health bias, which is often treated as a trait-level effect, reflects the mood that participants were in on the day of assessment—that is, a state affective bias.

Should this be the case, the potential medical issues stemming from reporting biases could be alleviated by providing a reporting context that promotes the optimal affective state for unbiased reporting. A state bias orientation would also be less likely to impact medical professionals’ judgments of a person’s character than would a trait bias assumption, potentially resulting in greater responsiveness of the physician to the
individual’s health needs. It is important, therefore, to consider whether state or trait affect is most predictive of biases in self-reported health on both the global and the daily level—which is reflected in Aim 2 of the present project. Although there are existing studies that have investigated affect-biased health perceptions on the state level, they tend to measure these processes at a single point in time, often within an experimental paradigm (e.g., Bogaerts et al., 2005; Wright, Ebrecht, Mitchell, Anggiansah, & Weinman, 2005), which makes it difficult to distinguish trait affect processes from state affect processes. A study by Watson (1988) came close to addressing the health bias effects of state (or daily) vs. trait affect as is done here, although that analysis was restricted to investigating symptom perception bias on the daily level; the sample in that study was also restricted to undergraduates, whereas the present study is aimed at exploring these processes in older adults. A preliminary study to the present project utilized the day-level health bias paradigm described here—although in a sample spanning early midlife to old age—and found evidence for both PA bias and NA bias (low- and high-arousal NA were considered separately) on the daily level, although PA bias emerged as most salient when both affective biases were considered (Whitehead & Bergeman, 2013); this study did not, however, investigate the impact of trait-level affect on these daily health bias processes. The present project is especially well-equipped to address these multi-level questions due to the longitudinal nature of the day-level data—being assessed over 56 consecutive days—and to the trait-level affect and health information being collected and operationalized separately from the day-level data. The theoretical models introduced next will serve to guide the state vs. trait investigation of both positively- and negatively-biased health perceptions.
1.3.1 Models of Health Bias

A number of explanations have been put forth in an attempt to explain the mechanisms that underlie the apparently persistent inaccuracy patterns in self-reported health. The *Symptom Perception Model* (Gijsbers van Wijk & Kolk, 1997) suggests that bias in self-reported health is a factor of the overall underlying process of information input → attention → detection → attribution → experience → behavior. Psychological hypersensitivity at any of these points (e.g., paying too much attention to a bodily sensation, failing to detect a symptom, misattributing a given sensation to either morbid or benign origins, inaccurately associating a symptom with a previous illness experience) can lead to an inaccurate perception of a given symptom, resulting in biased health reports. Empirical studies have supported this hypothesis; for example, in an attempt to rule out whether heightened symptom reports were in fact due to greater sensitivity to physiological sensations, Mailloux and Brener (2002) divided undergraduate participants into either heartbeat detectors or non-detectors based on their performance on a heartbeat detection task, and had both groups complete a scale designed to capture somatosensory amplification (over-perception of physical symptoms). Results revealed that heartbeat detectors had lower levels of symptom amplification, indicating that such bias is not related to how sensitive one is to their bodily sensations, and instead implicating a more psychological source of bias.

A second study, which looked at perceived heart function bias in individuals with a diagnosis of congenital heart disease (ConHD), found that those high in trait anxiety were more likely to report heart symptoms during an experimental stress manipulation, despite having objective heart function that did not differ from non-anxious ConHD
participants (Karsdorp et al., 2007). Watson and Pennebaker (1989) also discussed the Symptom Perception hypothesis in their review paper on the relationships between health, stress, and negative affectivity, reporting that the studies they reviewed partially supported this view—negative affectivity predicted subjective health even when objective health indicators and physical functioning were accounted for, indicating a significant psychological component. They concluded that negative affect is an important factor to take into account when using self-reported health measures.

A second hypothesized mechanism is described by the Cognitive-Affective Model (Janssens, Verleden, De Peuter, Van Diest, & Van den Bergh, 2009; Petersen, Van den Berg, Janssens, & Van den Bergh, 2011), which was initially developed based on the literature on under- and over-perception of symptoms in the context of asthma; the model is based on the assumption that health bias is not a trait characteristic, but rather a state or environmental response. Proponents of the model specifically suggest that external cues—information about what to expect and how one should feel emotionally—prompt reactions based on previous experiences with similar contexts. That is, in the case of asthma, asthma sufferers have an “asthma schema” based on their previous experiences with asthma symptoms and attacks; the schema is comprised of situational and affective cues that the individual deems relevant to his or her experience of asthma symptoms, such as stress, panic, the outdoors, and physical activity. This schema is activated when these cues are present, thereby increasing the individual’s sensitivity to breathing-related sensations and prompting feelings of negative affect (e.g., anxiety), which then biases him or her to report breathing problems even when objective indicators reveal that none exist. This schema-bias concept can be generalized to other symptoms as well, whether
they are experienced within the context of a specific diagnosis or are non-specific physical complaints.

It is interesting to note that affect is considered a primary factor in both of these theories, although the level at which the health bias process occurs differs in each. The Symptom Perception Bias theory assumes that trait-level negative affect is at work, resulting in consistently biased perceptions across contexts within a given individual. The Cognitive-Affective model takes a more state-based approach, assuming that it is the environment at the time of judgment—rather than the individual’s trait characteristics—that prompts an affective state, which is the primary predictor of biased health perceptions. By investigating the health-biasing effects of affect on both the global and the daily level, and by testing the extent to which the effects of trait- and state-level affect processes are distinct in the context of perceived health, the present project will inform the degree to which the assumptions of each theory are valid.

Some of the ideas of the symptom perception bias and cognitive-affective theories can be translated to the positive affect framework, but because they were primarily developed within the context of negative affect, and because positive affect and negative affect have been differentiated on both psychological and physiological levels (Watson et al., 1999), it is important to consider the processes underlying positive health bias separately from those related to negative affect. Although there is no theory explicitly outlining the role of positive affect per se on health bias, there are existing frameworks that can inform the current investigation. For example, theories of Optimistic Bias suggest that people believe that negative events or experiences are less likely to happen to themselves than they are to others (Helweg-Larsen & Sheppard, 2001; Klein & Helweg-
Larsen, 2002). In the present context, when subjective health evaluations include components of peer comparison, this would suggest that those higher in this optimistic bias will rate themselves as healthier than their peers; they consider any difference, if it really exists, to be greater (and more positive) than it actually is. Although this framework is primarily oriented in the future tense and is not directly relevant to current health ratings, trait optimism is strongly related to trait positive affect, and it is likely that this optimism can also lead to an under-reporting of symptoms and/or a denial of poor health.

Another personality characteristic that has been implicated more explicitly in biased health perceptions is defensiveness, which is a desire to be perceived by others in a positive manner. One study found that adults scoring higher on a trait measure of defensiveness were significantly more likely to under-perceive asthma symptoms than less defensive participants (Isenberg, Lehrer, & Hochron, 1997). Although defensiveness is distinct from positive affect, the two are associated with one another in that both are linked with higher levels of endorphins, also known as “feel good hormones” (Isenberg et al., 1997). So, there is evidence that positive aspects of personality or physiology contribute to biased symptom reporting in the form of either under-perception of symptoms (as opposed to the over-perception associated with negative affect), or through the counterbalancing of negative affect bias (Bogaerts et al., 2005). The sections that follow outline the empirical literature on affect-biased health perceptions at both trait and state levels, separately for negative and positive affect.
1.3.2 Negative Affect Bias

A review paper by Watson and Pennebaker (1989) strongly implicated negative affect—primarily high-arousal negative affect—in the persistent health biases observed in the self-reported health literature. In an earlier study, Watson (1988) also demonstrated that individuals high in trait NA reported significantly more physical complaints, even though their objective health indicators were comparable to those with lower trait NA. Several studies have also investigated this effect within an experimental context (Bogaerts et al., 2008; Bogaerts et al., 2005; Karsdorp et al., 2007; Mora et al., 2007; Strigo et al., 2008), consistently finding that trait NA is associated with biased health perceptions. Bogaerts and colleagues (2005) assigned people to high and low trait NA groups, and then randomly assigned members of each group to participate in breathing assessments (deep breathing, breathing frequency) in either an environment with a pleasant odor or one with a distressing odor. They found that participants in the high NA group were less accurate in their perceptions of the depth of their breathing in both conditions, but when it came to breathing frequency, accuracy declined only in the distressing condition, perhaps reflecting an “undoing” or counterbalancing effect of state PA on the impact of trait NA.

A second study, also using this breathing paradigm, divided participants into either high symptom reporters or low symptom reporters, based on their responses to a survey on medically-unexplained symptoms (MUS; Bogaerts et al., 2008). All participants were then randomly assigned to either a symptom frame, in which the breathing task was framed in terms of “symptoms” they would be feeling, or a sensation frame, in which symptom terminology was replaced with more neutral “sensation”
terminology. Results revealed that high symptom reporters were not necessarily inaccurate in their sensation perception, as they performed similarly to the low symptom reporters in the neutral sensation condition; in the symptom condition, however, which was more negatively valenced in terms of affect, high symptom reporters did demonstrate bias, over-perceiving the presence of physical sensations in the breathing task.

Activated negative affect—specifically trait anxiety—was also found to amplify the extent to which individuals with congenital heart disease perceived non-specific symptoms as heart symptoms during stress, as the increased heart symptoms could not be explained by objective measures of heart functioning (Karsdorp et al., 2007). Another study found trait negative affect to have a biasing effect in the context of ambiguous symptoms, but also noted that NA can promote accuracy in certain situations (Mora et al., 2007). The results indicated that individuals diagnosed with asthma who have higher levels of trait NA—and thereby worry more about and pay more attention to illness-related symptoms—were actually more accurate in reporting asthma symptoms and attributing them to asthma than those lower on trait NA. It may be that there is an “ideal” level of trait NA that promotes attentiveness to illness-specific symptoms without causing over-generalization and misperception of physical sensations. Non-activated, or low-arousal, negative affect—such as depression—has also emerged as a contributor to bias, although to a more limited extent than high-arousal negative affect such as anxiety. For example, a study comparing heat sensitivity in young adults with major depressive disorder (MDD) to young adults without depression found that those with MDD perceived brief heat stimuli to be more intense and more unpleasant than the non-MDD
group, suggesting a link between depressed affect and physiological hypersensitivity (Strigo et al., 2008).

Short-term, or state, negative affect also impacts the presence of biased health perceptions. For example, a study investigating the use of reliever medication in adults with asthma found that a person’s negative affect on a given day significantly increased the likelihood that reliever medication would be used that day, even when actual asthma symptoms were accounted for (Main et al., 2003). The authors concluded that being in a negative mood state makes it more likely that an individual will activate the negative asthma symptom schema, and thereby interpret ambiguous or arbitrary sensations as related to their diagnosis and requiring treatment. Another study found that participants reporting higher levels of state anxiety demonstrated a greater dissociation between actual and reported symptoms of acid reflux than those who were less anxious during the lab visit (Wright et al., 2005). An interesting state–trait distinction has also emerged in the context of anxiety; Zoellner and Craske (1999) found that intraindividual state anxiety—that is, having higher than typical levels of anxiety on a given day—predicted a more accurate perception of heart-beat features during a caffeine manipulation, whereas interindivdual differences in trait anxiety did not have an effect. These results may point to an interaction in which state affect either buffers or exacerbates the effect of trait affect on perceptions of certain physiological processes.

1.3.3 Positive Affect Bias

It is important to recognize that the majority of the literature on self-reported health bias—along with the theoretical models, as mentioned previously—is primarily oriented around negative affective processes. There has been much less investigation into
the role of positive affect, despite its apparent importance. Early on, Watson (1988) reported then-unexpected evidence for the potency of positive affect and self-reported health symptoms when he found a strong link between daily PA and physical symptom complaints, which was of comparable strength to the effect of daily NA. He also presented evidence for differential effects of affective arousal and valence characteristics, as participants experiencing a cold or flu on a given day reported lower levels of activated PA, but not higher levels of activated NA, indicating that people were generally more lethargic or unaroused on these days—and perhaps less happy—but not necessarily distressed. Note that, because both health and affect information were self-reported in a concurrent fashion, it is difficult to identify the directionality of this association; it may be that the reported cold or flu causes the more lethargic affect ratings, but it may also mean that low levels of PA—or higher levels of low-arousal NA—bias self-reports of health events in a more negative manner. This phenomenon is similar to one termed “effort after meaning,” in which individuals seek to explain something post hoc; for example, people may feel down or blue on a given day, and then conclude that they must be getting sick (Bartlett, 1995).

In their review paper on positive affect and health, Pressman and Cohen (2005) note that people high in trait PA tend to report fewer and less severe symptoms when they encounter morbidity, even when objective indicators of physical health are controlled; they conclude that these associations in the literature represent cognitive biases brought on by positive affectivity. Another study, aimed at investigating which factors are most predictive of an individual’s overall rating of health, found that higher initial PA was associated with less functional decline over time (Benyamini et al., 2000). The results
also demonstrated that higher levels of trait PA predicted better future self-reported health even when actual functional decline was accounted for, indicating the presence of a positive affect bias when it comes to one’s overall assessment of health.

Regarding state-level positive bias, the findings by Bogaerts and colleagues (2005) indicated that having higher levels of state PA can help to counterbalance the tendency toward inaccurate symptom perception in people with high trait NA, serving to promote accuracy and reduce bias. High-arousal state PA also led to an underreporting of symptoms in another study, which found that people with asthma are less accurate in their perception of actual reduced lung function after being positively aroused by a rollercoaster ride (Rietveld & Van Beest, 2006). Similar findings emerged from a study done with asthmatic children, in which an induced positive mood reduced their perception of asthmatic symptoms (Von Leupoldt, Riedel, & Dahme, 2006). The authors suggested that this may be beneficial, in that a positive stimulus may serve to calm and distract a child who is experiencing an asthmatic attack, but it may also be dangerous, as children may under-treat symptoms when they are positively aroused. Weisenberg and colleagues (1998) found an interesting delayed effect of induced positive affect in their study, in which participants were assigned to a control (no film) condition or had to watch either a humorous (PA) or holocaust (NA) film either 15, 30, or 45 minutes in length, followed by a pain paradigm. They found that those who watched the humorous film reported less pain, but only after a 30-minute waiting period, which the authors concluded was associated with the physiological timing of dopamine release.

Because it is more feasible to induce and investigate the impact of aroused positive affect than low-arousal positive affect, and perhaps because it is regarded as less
important, there is very little information available when it comes to the impact of lower-arousal positive affect on health and health bias. One repeated-measures study found that in men, the combination of high pleasure and low arousal at Time 1 predicted higher HDL ("good cholesterol") and lower triglycerides at Time 2, whereas the high pleasure/high arousal affect combination predicted lower HDL and higher triglycerides (Shirom, Melamed, Berliner, & Shapira, 2009). These findings indicate that pleasurable affective arousal can have a negative impact on lipid levels, at least for men. Pressman and Cohen (2005), in their review paper on PA and health, also stated that an important future direction in the field is to investigate the differential impact of activated vs. non-activated levels of PA. Although the present project does not aim to test for the specific effects of low-arousal affect, the expanded scales being used to measure positive and negative affect are intended to capture a broader range of affective arousal than is traditionally assessed.

1.3.4 Conceptualizing General Health Bias

It is important to note that the vast majority of the literature relating to affective health bias is specific in nature; that is, studies tend to investigate biases present for certain symptoms within particular diagnoses, such as those relating to asthma (Bogaerts et al., 2005; Janssens et al., 2009), heart function (Karsdorp et al., 2007), and diabetes (Schandry et al., 1996). This approach certainly makes it easier to assess the degree of bias, as there is usually a very precise objective measure available against which to compare subjective assessments. For example, in the case of breathing symptoms associated with asthma, participants’ perceptions of their breathing rate and depth can be directly compared to mechanical readings of his or her actual breathing rate and depth.
Similarly, heart patients’ subjective reports of heart rate or arrhythmias can be compared to objective heart readings taken concurrently. These symptom-specific methods get at affective health bias in a relatively straightforward manner, and provide important information regarding whether and to what degree positive and negative affect impact individuals’ health perceptions within a given disease or symptom context.

The specificity required by these approaches, however, also limits the generalizability of findings—do one’s affective biases in the context of heart symptoms translate to other health perceptions as well? Do these specific biases reflect a general bias profile, or are they restricted to the disease or symptom paradigm of greatest salience? Although the current project does not set out to address these questions directly, Aim 3 gets at this issue by investigating the presence of affective bias in a non-specific, general health context; this will permit the results to inform the extent to which global and daily affect impact individuals’ everyday health perceptions in normal, healthy older adults, external of specific diagnoses or symptom schemas. In the present project, this more broad-based conceptualization of health bias will be accomplished on the global level by taking a multi-systems approach to operationalizing global objective health, and using more general health assessments to tap global perceived health. Daily reports of positive and negative health events and ratings of overall health satisfaction will serve this purpose on the daily level.

1.3.5 Physiological, Neurobiological, and Behavioral Correlates of Affect

In order to fully understand the way in which affect can bias health perceptions, it is important to briefly acknowledge the direct influence that affect has on objective health. Although affect exerts its most demonstrable effects on indices of perceived
health, research demonstrates that a portion of the affect–objective health relationship is attributable to real effects resulting from neurological and physiological processes underlying positive and negative affect. Powell and colleagues (2008), for example, found that higher negative affect at Time 1 was associated with reduced functional ability six weeks later (controlling for functional ability at baseline). As noted in the previous discussion of affect, research has consistently linked affective experience with physiological and neurobiological processes. For example, neurological research has indicated that lesions or activations of differential brain regions are associated with either positive or negative emotional experience (Watson et al., 1999). Increases in positive affect are associated with release of the neurotransmitter dopamine, which facilitates working memory and problem solving processes (Ashby et al., 1999). PA is also associated with lower blood pressure and lower levels of the stress hormone cortisol (Davidson et al., 2010), as well as improved immune system function (Pettit et al., 2001); low-arousal PA has also been linked with more healthy lipid levels (Shirom et al., 2009). NA, on the other hand, has been linked with higher blood pressure (Ryff et al., 2006), higher levels of cortisol (Wright et al., 2005), and poorer immune function (Kiecolt-Glaser et al., 2002). Overall, the literature on affect and health indicates that positive affect tends to be predictive of healthier functioning in a number of physiological systems, whereas negative affect is associated with more deleterious health indicators and outcomes (Fredrickson, 2000; Pressman & Cohen, 2005; Steptoe et al., 2006; Steptoe et al., 2005). Although these links and associations do not necessarily represent causal processes, there is evidence that affect is not an island; other systems of the body impact and/or are impacted by emotional experience, making it important to acknowledge the
legitimate link between affect and objective health indices that must be controlled when attempting to assess bias in subjective health ratings.

1.4 Affect and Health Bias in Older Adults

Although the present study focuses on health bias in older adults, it is important to highlight how the presence and strength of these effects in an older adult sample may differ from those that have been found in younger samples. In a study on age differences in correlates and processes of positive and negative affect across adulthood, Windsor and Anstey (2010) address the consistent finding that affective well-being indicators tend to remain stable or even increase from young adulthood through at least the early years of old age, despite the inevitable declines in physical, cognitive, and social resources associated with aging (Ashby et al., 1999; Park-Lee, Fredman, Hochberg, & Faulkner, 2009). Termed the “paradox of well-being,” this phenomenon is consistently demonstrated with the positive and negative affect of interest here. For example, in their longitudinal study with young, midlife, and older adults, Windsor and Anstey (2010) found that although the initial levels of PA were highest for the young adult group, PA in the midlife and later life groups increased significantly over the course of the study; NA, on the other hand, was lowest in the oldest group, and both the young and midlife groups reported a significant decrease in NA over time.

This “paradox of well-being” has contributed to the development of *Socioemotional Selectivity Theory* (SST; Carstensen, 1995; Carstensen, Isaacowitz, & Charles, 1999), which suggests that a sense of dwindling time left motivates older adults to focus their resources on enhancing positive experiences and emotions while avoiding negative experiences and emotions. This hypothesis is supported by findings indicating
that older adults consistently report a higher number of positive events and a lower number of negative events than younger adults (Almeida, 2005; Charles et al., 2010; Mroczek & Almeida, 2004; Stawski, Sliwinski, Almeida, & Smyth, 2008). Research similarly indicates that older adults are more likely than younger adults to cognitively reframe negative aspects of a situation into neutral or positive ones (Benyamini et al., 2000). Studies have also demonstrated that affect—particularly positive affect—is an especially important feature of subjective well-being in later life (Hicks, Trent, Davis, & King, 2011). Perhaps paradoxically, neurological research has demonstrated that levels of dopamine—the hormone most closely associated with PA along with cognitive processing—decline by 7-8% every 10 years (Ashby et al., 1999); this fits with the literature showing reduced cognitive flexibility with age, but conflicts somewhat with the higher levels of PA reported by older adults. It therefore may be that the mechanism linking PA and dopamine breaks down with age, while PA itself maintains its effects through alternate mechanisms.

When it comes to age differences in affective arousal, existing research indicates that high-arousal negative emotions decrease in frequency with age, while emotions with lower-arousal features become more frequent and/or more frequently recognized and labeled (Windsor & Anstey, 2010). Some have suggested that older adults experience more complex, or nuanced, emotions, which are potentially more representative of the entire affective valence/arousal space (e.g., Magai, Consedine, Krivoshekova, Kudadfi-Gyamfi, & McPherson, 2006). Others, however, argue that emotional experience becomes less complex with age, as older adults—facing decreasing cognitive flexibility—attempt to optimize positive emotions and restrict the arousal range of
emotional experience to more moderate levels (Labouvie-Vief, 2003; Labouvie-Vief, Hakim-Larson, DeVoe, & Schoeberlein, 1989). The greater salience of lower-arousal affect to older adults’ affective identity and experiences is one of the primary reasons for the inclusion of the lower-arousal positive and negative affect terms in the affect measures used in the current project. In the present context, the assumptions of SST and the existing affect–age literature predict that positively-valenced affect will have especially pronounced effects in the later life sample being used here. The reframing aspect may also mean that participants in the current study are more susceptible to positive affect biases in symptom reporting and ratings of overall health.

Along with the age-related affective changes discussed above, there is evidence for age-related differences in the presence of self-reported health biases. Although some research has shown that older adults are more likely to label physical symptoms as stemming from diseases commonly associated with aging, leading them to over-report their symptoms (Kriegsman, Penninx, Van Eijk, Boeke, & Deeg, 1996), the majority of the literature indicates that older adults are more likely to under-perceive and/or under-report physical symptoms than adults at earlier points in the lifespan. Research has shown that the threshold of pain or loss of function that must be met before older adults seek treatment is higher than is required for younger adults (Yong, Gibson, Horne, & Helme, 2001); this may be due to the perception that some level of pain and disability is “normal” in later life (Lagaay, Van der Meij, & Hijmans, 1992), the desire to not be perceived as a burden by a spouse or family member (Yong et al., 2001), or less confidence in the accuracy of their own perceptions of physical sensations (Yong et al.,
These issues are generally more likely to impact reports of physical symptoms and treatment-seeking behaviors than the ratings of overall health used in the present study, which have lower stakes—in terms of social acceptance and medical consequence—due to the confidential, non-medical context in which they are given. On the other hand, the stereotype factor, or the belief that a degree of poor health is normative in later life, can potentially confound the effect of PA bias; this is especially the case when the referent group for self-rated health is comprised of other older adults with a relatively lower level of health than the general population of adults. In an effort to account for this, one of the items measuring perceived health on the global level asks for a rating in comparison with one’s peers; the inclusion of this item should reduce the age comparison bias that may otherwise be present in a non-referent overall health rating.

Overall, it is important to investigate the role of affect bias—particularly PA bias, which is most likely to be present considering the tendency of older adults to over-rate their health—in later life, as it provides a potentially adaptive perspective on this phenomenon. That is, whereas the factors discussed above imply physical, social, and cognitive declines which then result in maladaptive health biases, the role of PA—which is generally associated with better physical and mental health (Benyamini et al., 2000; Pressman & Cohen, 2005)—may indicate that biased health perceptions can be adaptive in later life, perhaps serving to boost subjective well-being and mental health or motivating individuals to maintain a more active or engaged lifestyle than they would otherwise.

Note that, although empirical findings in this area have been relatively consistent over the past few decades, it is still unclear whether these patterns represent age effects, or simply reflect the cultural norms and expectations of the latest generation(s) of older adults; this makes longitudinal studies in this area an important future endeavor. Regardless, these issues are assumed to be applicable to the sample of older adults used in the present project.
1.5 Present Study

1.5.1 Aims and Contributions

As evidenced from the research presented above, there are a number of gaps in the existing literature on health bias, including the tendency to limit investigations to the biasing effects of negative affect or high-activation affects; the lack of work looking at how affective health bias operates on the global vs. the daily level; and the limited generalization of existing findings due to their diagnosis- or symptom-specific paradigms. The present study is designed to address these issues, with three Aims contributing to the existing literature by 1) establishing that the full spectrum of affect—including both positive and negative affects reflecting a broad range of affective arousal—is important to consider in the context of health bias; 2) addressing the issue of whether affect-related health bias is primarily a state factor (i.e., determined by a person’s mood at the time of assessment), a trait factor (i.e., determined by a person’s personality, unrelated to circumstances at the time of assessment), or some combination of the two; and 3) establishing the presence and process of general (not diagnosis- or symptom-specific) health bias on both the trait (global) level and the state (daily) level in a community sample of older adults. This was accomplished via three phases of analysis: the first investigated the presence of positively- and negatively-biased health perceptions on the global level, controlling for objective health; the second explored the presence of positive and negative health bias on the daily level, controlling for daily health events; and the third compared the effects of global and daily affect so as to conclude whether they represent different processes or are simply reflections of one another on their respective levels of analysis. The final piece is the most applied contribution of the study,
as the findings can be used by physicians and researchers to take steps to improve accuracy and reduce bias during self-reported health assessments.

1.5.2 Analytic Overview

The initial analytical step will be to run exploratory and confirmatory factor analyses to identify the structure of affect in the data, and to ascertain whether two factors (positive and negative) are sufficient to describe the affective space, or if additional domains are necessary to capture the broader range of activation represented by the expanded affect items. This will be done separately for global and daily affect in order to capture any level differences that exist. The scales that emerge from the factor analyses will then be used to explore how different levels of these affective experiences impact global and daily health perceptions. Specifically, a) whether the affective factors moderate the relationship between objective measures of overall health and subjective health perceptions on the global level; and b) whether the daily affective variables moderate the effect of a given day’s negative health events on that day’s overall assessment of health satisfaction. Significant moderation implies that an individual’s affective tendency (for the global analysis) or state (for the daily analysis) significantly impacts—or biases—his or her global and daily perceptions of health, respectively.

After establishing the global and day-level effects, it is important to test them against one another—do the day-level effects simply reflect the global affect tendency, or is there a unique contribution of one’s affect on the daily level? Likewise, does the level of affect-related health bias present on the daily level for a given individual explain the link between affect and health bias at the global level? Thus, a the present project also investigates the extent to which the global and daily affective bias effects reflect the same
underlying process, or are processes that are separate and indicative of level-specific effects.

1.5.3 Hypotheses

Based on the rationale presented thus far, the formal hypotheses guiding the analyses were as follows:

Affect. Both daily and global affect items would split into two primary factors (PA and NA) when submitted to an exploratory factor analysis; confirmatory factor analysis would demonstrate this two-factor structure to be a good fit to the daily and global affect data. All four affect scales (global and daily PA and NA) resulting from the factor analyses are expected to be moderately correlated with one another in the sample.

Global Health Bias. Each of the measurement models for global Objective Health, Perceived Health, and Positive and Negative Affect described in the Method section were expected to demonstrate a good fit to the data and be appropriate for use in the structural models. Concerning the structural models, Objective Health was expected to positively predict Perceived Health, as one’s health perceptions are likely to be generally reflective of one’s actual health. Once the affect factors were included as moderators, it was expected that a) PA would reduce the effect of Objective Health on Perceived Health, indicating the presence of positive affect bias; b) NA would exacerbate the effect of Objective Health on Perceived Health, indicating the presence of negative affect bias; and c) when both PA and NA were included as simultaneous moderators, the effect of Objective Health on Perceived Health was not expected to be substantially different from the baseline model, as PA was hypothesized to ameliorate, or “undo,” the negative biasing effect of NA (Fredrickson, 1998). Based on the literature demonstrating
a link between affect and objective health cited above, the affect factors were hypothesized to be correlated with the Objective Health factor (negative correlation for PA, positive correlation for NA); the NA and PA factors were also expected to have a moderate negative correlation with one another in the combined moderation model.

**Daily Health Bias.** On the daily level, it was expected that a given day’s health events—in which higher counts indicate more negative events and fewer positive events—would be negatively predictive of that day’s health satisfaction. Concerning the affect moderators, PA on a given day was hypothesized to reduce the negative relationship between that day’s health events and health satisfaction; NA, on the other hand, was expected to exacerbate that effect. When both PA and NA were included as moderators on the daily level, daily PA was expected to counteract the negative biasing effect of daily NA, as was predicted on the global level.

**Trait vs. State Bias.** There is some evidence that the processes underlying the biasing effects of NA stem from more trait-level characteristics, whereas the biasing effects of PA manifest within more state-level affective contexts and experiences (Watson, 1988); this led to the prediction that trait NA would be a better (or equivalent) predictor of daily health bias than day-level NA, whereas day-level PA was expected to out-perform trait PA in predicting biased health perceptions on the daily level. In terms of the trait vs. state global models, the same rationale led to the predication that day-level PA bias would mediate the effect of trait PA on global health bias, whereas trait-level NA would retain its effect when day-level NA bias is added to the model.
CHAPTER 2

METHOD

2.1 Participants and Procedure

Participants were drawn from the sample of the Notre Dame study of Health & Well-Being (NDHWB; original sample N = 778), which is a 5-year longitudinal study primarily aimed at investigating stress and resiliency processes in midlife and older adults; it is comprised of yearly questionnaires in Years 1-5, 56-day daily diary surveys in Years 1, 3, and 5, and qualitative interviews on a subsample of participants in Years 2 and 4. All potential NDHWB participants were identified via lists of middle-aged and older adults from the Northern Indiana area purchased from a market research firm and based on census data and the Survey of Residential Households. Those who expressed interest in participating received a consent form along with the first yearly questionnaire in the mail, which they completed and returned to the researchers at their convenience in a postage-paid envelope. Participants who expressed interest also took part in the 56-day daily diary “bursts,” which were received by mail on a fixed schedule, completed each night before going to bed, and returned 1-3 weeks at a time via postage-paid envelopes. Participants received remuneration for each portion of the study completed ($20.00 a year for the yearly questionnaire, $10.00 per week for the daily diary, and $30.00 for the interview). In Year 5, the later life cohort of the NDHWB has a total of 267 participants ranging in age from 58 to 91 (M = 71.9, SD = 4.6); 207 of those have participated from
Year 1, whereas the rest have been added along the way in order to counter the effect of attrition; 248 of Year 5 participants participated in the Year 5 daily diary.

In order to supplement the rich survey and interview data of the NDHWB with more objective measures of health in later life, 153 participants aged 55 and older were also recruited for participation in an in-person health battery in Year 5, which was conducted by a registered nurse (the blood draw was performed by a trained phlebotomist from the South Bend Medical Foundation). This health battery included: 1) a health interview asking for detailed information about each participant’s physical health, as well as their personal and family medical history and their health-related lifestyle behaviors; 2) a basic physical, collecting health indicators such as blood pressure, heart rate, height/weight, and peak flow capacity; 3) a functional assessment, which evaluated gait, balance, and ability to complete tasks of everyday living; 4) a brief assessment of cognitive functioning, 5) a blood draw, to assess physiological indicators of metabolic, cardiovascular, and immune function; and 6) a release of medical records, which were subsequently requested and obtained from each participant’s primary physician. The blood draws were conducted and analyzed by South Bend Medical Foundation (SBMF) in accordance with American Drug Administration regulations and guidelines; SBMF returned results of tests for the following physiological indicators: C-reactive protein, low-density lipoproteins (LDL cholesterol) and high-density lipoproteins (HDL cholesterol), triglycerides, homocysteine, hemoglobin a1c, dehydroepiandrosterone-sulfate (DHEAS), and interleukin-6; blood results were also sent to the participant, as well as to his or her primary physician with participant consent. Subjects received $100
in exchange for their participation in the health battery, which generally took about two hours to complete.

Participants of the present project were the 153 older adults who participated in the in-person health battery, provided they filled out at least a portion of the daily diary surveys in Year 5, and completed the global questionnaire packet in Year 5. The participants ranged in age from 56-82 years (M = 71.2); 63% were female; 44% of participants are married, 24% are widowed, 23% are divorced or separated, and 9% are single; 97% have at least a high school education, and 36% have a college degree; the sample is 88% Caucasian, 7% African American, 2% Hispanic or Latino, 1% Asian or Pacific Islander, and 2% Other. When it comes to income, 1% make less than $7,500 annually, 15% earn between $7,500 and $14,999, 22% earn between $15,000 and $24,999, 28% earn between $25,000 and $39,999, 24% earn between $40,000 and $74,999, 5% earn between $75,000 and $99,999, and 5% earn $100,000 or more. These demographic characteristics reflect those of the Northern Indiana population from which participants were drawn. Because the in-person assessment involves the participant coming into the lab, however, the members of the present sample tended to live closer to the lab, and have higher levels of physical function, than those who did not elect to participate. We attempted to reduce these potential differences by offering rides to and from the lab to all participants, regardless of their location in the region.
2.2 Measures

2.2.1 Global Measures

On the global level, variables of interest included trait positive and negative affect, objective indicators of health, and subjective indicators of perceived health.

*Trait affect.* A form of the Positive and Negative Affect Schedule (Watson et al., 1988), with the 20 original high-activation items (e.g., angry, excited) augmented with 8 moderate- and low-arousal affect terms (e.g., relaxed, depressed), was used to assess affective experience on the global level. Participants were asked to report “the extent to which you generally feel each emotion” on a scale from 1 (*Not at All*) to 5 (*Extremely*). It was expected that these 28 items would separate into distinct PA and NA factors when examined via exploratory factor analysis (EFA), thereby reflecting a broader range of positive and negative affective experience than high-activation-only scales. Completion rates for these individual affect items on the global level in the present sample ranged from 98-100%.

Although individual affect items were used as manifest indicators of the latent PA and NA factors in the global analysis, scale versions of the trait PA and NA variables were used in the day-level analysis. Omitting items dropped during the analyses (see detailed explanation in Results), the possible range of the global PA scale (13 items) was from 13 to 65 ($\alpha = .91$), whereas that of the NA scale (11 items) was from 11 to 55 ($\alpha = .93$). A 20% missing data rule was applied so that participants missing more than two items for either the positive or negative affect were counted as missing the relevant affect scale (e.g., missing more than two PA items = missing on PA); mean substitution was used to fill in scales for those missing two items or fewer. Note that the scale form of the
global affect items was only used in the day-level analyses. Completion rates for the 152
individuals with day-level data were 98.5% for trait PA and 99% for trait NA.

**Objective health.** A battery of physical and physiological indicators was used to
indicate participants’ objective health, with the system breakdown primarily drawn from
that utilized by Seeman et al. (2010) in the context of allostatic load; all physiological
measures were treated as continuous variables and were converted to z-scores to facilitate
standardization; all indicators were also coded so that higher scores were associated with
poorer health. Literature on the importance of each system (metabolic, cardiovascular,
and immune) and their respective associations with overall health is briefly discussed
below.

**Metabolic System.** The degree to which one’s metabolism is functioning properly
is strongly indicative of overall health and a reduced risk of both cardiovascular disease
and diabetes. Although single indicators of metabolic function are informative, research
has indicated that having unhealthy levels of multiple metabolic indicators is especially
predictive of morbidity and mortality. These findings have led to the conceptualization of
a *metabolic syndrome*, which is a clustering of factors that increase one’s risk for
developing cardiovascular disease and other maladaptive health outcomes (Muntner, He,
Chen, Fonseca, & Whelton, 2004; Seeman et al., 2010). These include waist-to-hip ratio,
cholesterol, triglycerides, and glucose levels.

**Waist-to-hip ratio.** Waist-to-hip ratio (WHR) is an indicator of obesity—
specifically of an accumulation of adipose tissue around the abdomen—and is simply the
circumference of the waist divided by the circumference of the hips (Dobbelsteyn,
Joffres, MacLean, Flowerdew, & The Canadian Heart Health Surveys Research Group,
Higher ratios indicate greater health risks, as abdominal obesity has been associated with the development of both diabetes and cardiovascular disease (Dobbelsteyn et al., 2001; Vazquez, Duval, Jacobs, & Silventoinen, 2007). In the present sample, 98.5% of individuals had complete waist-hip ratio data.

Cholesterol and triglycerides. Cholesterol is a fatty substance present in the blood that can become detrimental to health if it exists in too great a quantity and begins to build up in the arteries; cholesterol levels are primarily indicated by the presence of high-density lipoproteins (HDL; values higher than 60 are considered high) and low-density lipoproteins (LDL; values less than 100 are optimal) in the blood (Birtcher & Ballantyne, 2004). Higher levels of HDL cholesterol, also known as “good cholesterol,” have been shown to reduce the risk of developing blockages in the arteries; whereas higher levels of LDL cholesterol, also termed “bad cholesterol,” are known to increase that risk. The plaque buildup in arteries resulting from unhealthy cholesterol levels is strongly predictive of heart disease, heart attack, stroke, and some types of cancer, as well as a general decline in overall health and functioning (Birtcher & Ballantyne, 2004; Lorenzo, Williams, Hunt, & Haffner, 2007; Steenland, Nowlin, & Palu, 1995). Important information can also be gleaned by accounting for the relationships between levels of LDL and HDL cholesterol, done by calculating the cholesterol ratio (total cholesterol/HDL cholesterol); note that total cholesterol is simply the sum of LDL and HDL values. Ideally, the ratio should be 3.5:1 or lower, but anything below 5:1 is within the acceptable range (American Heart Association, 2013).

Triglycerides are another type of fat present in the body, and are generally measured along with cholesterol in order to get a more complete picture of the fat that is
present in the blood; higher triglyceride levels (values lower than 150 are considered normal) increase one’s risk of developing heart disease or having a stroke (Bircher & Ballantyne, 2004). All participants had complete lipid panel data.

Hemoglobin a1c. Elevated levels of fasting glucose are indicative of impaired metabolic function, and very high levels lead to a diagnosis of diabetes (Muntner et al., 2004). Glycosylated hemoglobin (hemoglobin a1c) is an indicator of glycemic control related to fasting glucose levels; it provides information about the average level of glucose in the blood over the past two to three months, with elevated levels (above 7%) indicating poorer glycemic control and heightened risk for diabetes (Calisti & Tognetti, 2005). In the present sample, 99% of individuals had complete hemoglobin a1c data.

Cardiovascular System. Although metabolic functioning is strongly associated with the development of future cardiovascular disease, indicators of heart function provide a direct assessment of current cardiovascular performance, as well as overall health. Indicators used here include heart rate, and blood pressure.

Heart rate. A more rapid heart rate—or the number of times the heart beats per minute—has been identified as a risk factor for a number of negative health outcomes, including heart disease and cancer (Greenland, Daviglus, Dyer, Liu, Huang, Goldberger, & Stamler, 1999; Steenland et al., 1995), as well as all-cause mortality (Greenland et al., 1999; Peters et al., 1999).

Blood pressure. Blood pressure is an index of how efficiently the heart is functioning; because blood pressure rises and falls with the beating of the heart, it is important to take multiple assessments—typically five minutes apart—to get an accurate reading. The two components of a blood pressure reading are systolic blood pressure
(SBP; values less than 140 are considered normal for older adults), or the pressure when the heart muscle contracts, and diastolic blood pressure (DBP; values less than 90 are considered normal for older adults), or the pressure when the heart muscle relaxes between heartbeats (American Heart Association, 2011; Psaty et al., 2002). Although elevated levels of both types of blood pressure are predictive of maladaptive health outcomes, higher levels of SBP are most closely related to cardiovascular disease and stroke. SBP has also been shown to increase naturally with age, making it especially important to consider in the present context (American Heart Association, 2011; Chobanian et al., 2003; Psaty et al., 2001). Hypertension is defined as having either SBP or DBP significantly above normal levels; very high blood pressure readings are indicative of a hypertensive crisis, which requires immediate medical treatment if an acute myocardial event is to be avoided (American Heart Association, 2011). Although not directly related to diabetes, high blood pressure frequently co-occurs in diabetic persons, which has been shown to exacerbate the risk for, and progression of, both diabetes and cardiovascular disease (Chobanian et al., 2003). In the present sample, 98.5% of participants had complete heart rate and blood pressure data.

Homocysteine. Primarily acquired through ingesting meat proteins or consuming alcohol, the amino acid homocysteine has been identified as an independent risk factor for cardiovascular disease. High blood levels of homocysteine are associated with arterial hardening and an increased risk for blood clots and stroke, and thus indicate poorer cardiovascular health (American Heart Association, 2012; WebMD, 2012). All participants had complete homocysteine data.
**Immune Function.** Immune function is an important indicator of current health, as the degree to which one’s immune system functions properly is directly related to how healthy he or she is currently, as well as how at risk he or she is for developing future infections or health conditions. Immune indicators used here include interleukin-6, C-reactive protein, and DHEAS.

Interleukin-6. Immune function is regulated by cellular proteins called *cytokines*, which are either pro-inflammatory or anti-inflammatory in function; as their name implies, pro-inflammatory cytokines such as interleukin-6 (IL-6; levels from 0-5 pg/mL are considered normal, whereas levels above 5 pg/mL are high) promote inflammation, which is an adaptive immune response in the short term, but can be detrimental if present for too long, as in the case of chronic conditions (Kiecolt-Glaser et al., 2002; South Bend Medical Foundation, 2012). Research has found the presence of chronic inflammation—and elevated IL-6 levels—to be a risk factor for the development and progression of diabetes (Pradhan, Manson, Rifai, Buring, & Ridker, 2001), cardiovascular disease (Volpato et al., 2001), and certain cancers (Kiecolt-Glaser et al., 2002), as well as all-cause mortality (Harris et al., 1999). Only one person was missing IL-6 information.

C-reactive protein. C-reactive protein (CRP; levels greater than 0.22 mg/dL are considered elevated), the production of which is stimulated by IL-6, is another indicator of prolonged inflammation; higher CRP levels have been associated with increased morbidity and mortality related to diabetes, heart disease, stroke, and cancer (Harris et al., 1999; Kiecolt-Glaser et al., 2002; Pradhan et al., 2001; Volpato et al., 2001). All participants had complete CRP data.
DHEAS. Dehydroepiandrosterone-sulfate (DHEAS; levels between 16 and 200 ug/dL are considered normal, although this range reduces to 14-180 ug/dL for post-menopausal women) is a steroid hormone that originates from the adrenal cortex (South Bend Medical Foundation, 2012). Because DHEAS levels peak in young adulthood and then steadily decline into old age, it is considered by some to be an index of aging (Goldman & Glei, 2006; Salimetrics, 2008). Lower levels of DHEAS have been associated with a number of diagnoses, including heart disease and diabetes, with links especially strong with conditions associated with age, such as cognitive impairment and physical disability (Glei, Goldman, Weinstein, & Liu, 2004). Although the mechanism underlying the link between DHEAS and health outcomes is still unclear, research has indicated that much of the benefit of DHEAS occurs through its function within the immune system (Goldman & Glei, 2006; Salimetrics, 2008), which is why it will be used for this purpose in the current project. All participants had complete DHEAS data.

**Diagnoses.** In addition to the physiological risk factors of disease outlined above, an individual’s actual diagnoses—specifically those of cardiovascular disease, diabetes, stroke, cancer, and hypertension—will be obtained from his or her medical records and will inform the objective health construct in the present project. Along with being the diseases most directly predicted by the physiological indicators being used in the present project, these diseases are among the most prevalent in the United States, and are also those most closely linked with mortality in older adults (Mokdad et al., 2003; Ong, Cheung, Man, Lau, & Lam, 2006; Wilson et al., 1998; Wolf, D’Agostino, Belanger, & Kannel, 1991); for this reason, they are referred to here as the “Big Five Diagnoses.” The diagnosis variable will be a count variable, so that a score of 5 indicates the presence of
all five diagnoses of interest, whereas a score of 0 reflects their absence. Medical records information was complete for 94% of participants.

*Perceived Health.* The items used to assess overall global perceived health are as follows: *How would you rate your general health status,* rated on a 4-point scale (*1* = excellent, *4* = poor); and *How would you rate your present health status compared to 5 years ago,* and *How would you rate your health status compared to others in your age group,* both rated on a 3-point scale (*1* = better, *2* = about the same, *3* = worse). In the present sample, each of these items had a 99% completion rate.

In addition, a somatic health measure assessing self-reports of non-specific physical complaints—such as shortness of breath, back pain, frequent headaches, and joint pain—will capture the physical complaints often correlated with health perceptions and not necessarily indicative of objective health. The 12 items are in a checklist form (Belloc, Breslow, & Hockstim, 1971), and the measure will be treated as a count variable, so that all *Yes* responses are scored as *1* and all *No* responses receive a score of *0*. A total score of *0* indicates no somatic health complaints, whereas higher scores indicate more somatic health problems. Participant data was 95% complete on this variable.

### 2.2.2 Daily Measures

On the daily level, constructs measured included daily positive and negative affect, daily endorsement of positive and negative health events, and daily overall appraisals of health events.

*Daily affect.* The augmented PANAS (Watson et al., 1988) described above also assessed positive and negative affect (PA/NA) on the daily level; the original scale format was adapted for daily use by using a “Today I felt…” prompt, followed by the list
of 14 positive and 14 negative affect descriptors. Participants rated each item on the extent to which they experienced it over the course of a given day, from 1 (Not at All) to 5 (Extremely). As was the case with trait affect, it was expected that EFA will identify a 2-factor PA/NA solution; after omitting variables that failed to load in the factor analyses, the possible scale range for PA (13 items) was 13-65; that for NA (11 items) was 11-55. Reliability alphas were calculated on the same ten randomly-selected days as were used for the EFA analyses described in Chapter 4: for daily PA, these ranged from .91 (Day 1) to .96 (Day 44), with an average alpha of .946; for daily NA, the range spanned from .90 (Day 47) to .96 (Day 9), with an average alpha of .932. The 20% missing data rule with mean substitution was again applied, so that missing more than two items for PA or NA on a given day resulted in the PA or NA scale being counted as missing for that day. The daily PA scale was 92% complete across person-days; for the daily NA scale, the completion rate was 92.5%.

Daily health events. Each day, participants reported whether or not any of four negative health events (I suffered a minor physical injury (minor cut or bruise), I had to see a doctor, I had allergy symptoms, and I had a cold or flu) and two positive health events (I exercised to improve my health and I ate a healthful diet) occurred on that day. In order to utilize both positive and negative health information and get a better picture of a participant’s “objective health” on a given day, the items were combined into a single Health Events scale, with positive health events reverse-scored so that they each effectively count as (-1) in the daily health events count. Thus, people could report anywhere from zero to 6 health events on a given day; the range of possible counts, however, ranges from -2 to 4, so that a score of -2 indicates the endorsement of both
positive health events and zero negative health events, whereas a score of 4 reflects the endorsement of all four negative health events and zero positive health events. All health events were drawn from the Inventory of Small Life Events (ISLE; Zautra, Guarnaccia, & Dohrenwend, 1986). Participants were coded as missing on health events on a given day if they failed to endorse either Yes or No for the entire health events scale. In the present sample, 92% of person-days had complete health event data.

Daily health assessment. After endorsing any health events that occurred on a given day, participants were asked “Overall, how satisfied were you with your health today?” They rated this statement on a scale from 1 (Not at All) to 5 (Extremely). The “satisfied” item was used as a daily general perceived assessment of health in the daily health bias analyses. The health satisfaction variable had a completion rate of 90% in the present project.
CHAPTER 3

ANALYTIC DESIGN AND RATIONALE

3.1 Preliminary Analysis

3.1.1 Establishing Affect Scales.

Because the affect data includes eight items not in the original PANAS—which separates into positive and negative activation scales—the initial step in dealing with affect will be to conduct an exploratory factor analysis (EFA) on the global and daily affect items in order to confirm that the factor structure still adheres to the expected PA and NA breakdown; as a general rule, items with factor loadings below .3, or which load onto a factor with fewer than three high-loading items, will be dropped.

3.1.2 Establishing Physiological Systems Variables

Because using the diverse objective health variables—cholesterol, heart rate, glucose levels, waist-to-hip ratio, medical diagnoses, and so on—provide information on a variety of physiological systems, and because the dispersion of indicators across these systems is somewhat uneven, the decision was made to group the measures by system, using EFA to identify the appropriate system factors. Each indicator was then standardized (M = 0, SD = 1) and summed with like items to form a system-level composite variable. For example, waist-to-hip ratio, body mass index, and hemoglobin
a1c were expected to form the Metabolic system variable, with higher values indicating more unhealthy system function (based on Seeman et al., 2010). These composite scores were then standardized (M = 0, SD = 1) themselves prior to their use as the four manifest indicators for the latent objective health factor.

3.2 Analysis 1: Global Health Bias

Because this sample size is on the boundary of being appropriate for the planned analytic methods (e.g., Anderson & Gerbing, 1988), the loss of any participant data due to missingness on one or two indicators is undesirable. Therefore, in the global analysis, maximum likelihood estimation (an analytic option available in the MPlus statistical package) was used to capitalize on all of the available data from each participant. The questions concerning global health bias were tested using a structural equation modeling (SEM) approach, which uses observed (or manifest) variables as indicators of unobserved (or latent) constructs. This approach has advantages over traditional regression methods, which recommend its use in the present project. First, SEM permits the researcher to account for measurement error by modeling error terms for observed indicators; this leads to more valid and reliable estimates than would be possible if such measurement error was not accounted for. A second advantage is that SEM not only allows the use of multiple indicators for a given construct, but also models differential weightings (or loadings) of the effects of each indicator on the latent construct—this gives the researcher information about how each indicator informs the latent factor that is not available when a composite variable approach is used in regression. Because the objective and subjective health constructs of primary interest are each measured by multiple—and in the case of objective health, multi-dimensional—indicators, the latent modeling approach will yield
more appropriate estimates to inform the research questions of interest than would a regression or path analysis approach using only manifest variables.

The traditional two-step approach recommended by Anderson and Gerbing (1988) was followed, in which confirmatory factor analysis (CFA) was used to first establish the validity of the measurement models for each latent factor, after which the overall structural models were tested. All indicator variables were standardized (M = 0, SD = 1), so as to aid in interpretation. The specifics of the measurement models are described first below, followed by a presentation of the structural models. All latent variable models were tested using the Mplus statistical package (Muthen & Muthen, 1998-2010). The fit indices for all measurement models were evaluated against accepted goodness-of-fit values (e.g., an RMSEA statistic < 0.05 and a CFI value at or above 0.95 would indicate very good fit; Schermelleh-Engel, Moosbrugger, & Muller, 2003); good model fit would provide evidence that the factor so conceived is appropriate for use in the subsequent structural models.

3.2.1 Measurement Models

*Objective Health.* The manifest indicators of the latent Objective Health factor were composite variables representing the Metabolic system, and the lipid and pressure components of the Cardiovascular system (based on the results emerging from the initial physiological EFA described above), as well as a variable indicating diagnostic status on each of the “Big 5” diagnoses. The equations for the Objective Health measurement model are shown below, in which \(MB\) is the metabolic system variable, \(CV_{\text{LIPID}}\) is the lipid variable, \(CV_{\text{PRESR}}\) is the blood pressure variable, \(DG\) is the diagnosis variable, and \(OH\) is the latent observed health factor:
MB = \xi_{OH} + \epsilon_{MB} \tag{1a}

CV\_LIPID = \lambda_{LP}\xi_{OH} + \epsilon_{LP} \tag{1b}

CV\_PRESR = \lambda_{PR}\xi_{OH} + \epsilon_{PR} \tag{1c}

DG = \lambda_{DG}\xi_{OH} + \epsilon_{DG} \tag{1d}

As shown in the corresponding figure, the loading of the MB variable is fixed at 1 in order to scale the latent factor and permit convergence; it is thus defined by the latent factor variance (\xi_{OH}) and the error term (\epsilon_{MB}) shown in equation 1a. Factor loadings (\lambda_{LP}, \lambda_{PR}, and \lambda_{DG}) are estimated for the remaining indicators, which are defined by the product of the respective factor loading and the variance of the latent factor (\xi_{OH}), as shown in equations 1b-1d. Significant factor loadings would establish the four indicator variables as valid measures of the latent Observed Health construct.

*Perceived Health.* Within the SEM framework, the latent Perceived (or Subjective) Health factor was indicated by 3 single-item measures (overall rating on a 4-point scale, and past- and peer-comparisons on a 3-point scale), and a self-reported somatic health variable. The decision to use single-item indicators in favor of a composite rating/comparison indicator (i.e., the 3 single items would be combined to form a single scale) was based on the theoretical assumption that each of these items gets at a different aspect of one’s perceptions of his or her health; these differential effects were therefore modeled using individual loading parameters. The measurement model equations for the Perceived Health factor are shown below, where RATE is the overall rating variable, PAST is the past comparison variable, PEER is the peer comparison variable, SOMH is the somatic health variable, and PH is the latent Perceived Health factor:

\[
RATE = \xi_{PH} + \epsilon_{RATE} \tag{2a}
\]
As was the case for the Objective Health factor, the loading for the RATE indicator was fixed to 1 (equation 2a), whereas the rest of the loadings on the Perceived Health factor ($\lambda_{PAST}$, $\lambda_{PEER}$, and $\lambda_{SOMH}$) were estimated (equations 2b-2d). The ($\xi_{PH}$) term represents the variance of the Perceived Health factor, and the error terms ($\epsilon_{RATE}$, $\epsilon_{PAST}$, $\epsilon_{PEER}$, and $\epsilon_{SOMH}$) reflect the residuals of each indicator. Once again, significant factor loadings would establish the four indicator variables as valid measures of the latent Perceived Health factor.

Affect. The latent factors of PA and NA were each indicated by the appropriate set of affect terms identified in the factor analyses described above; once again, all items were standardized (M=0, SD=1) prior to model estimation. Selected representative equations for the PA and NA measurement models are below:

$$PA_{active} = \xi_{PA} + \epsilon_{PAinterested}$$  
$$PA_{excited} = \lambda_{PAexcited} \xi_{PA} + \epsilon_{PAexcited}$$  
$$NA_{hostile} = \xi_{NA} + \epsilon_{NAdistressed}$$  
$$NA_{afraid} = \lambda_{NAafraid} \xi_{NA} + \epsilon_{NAafraid}$$

The factor loadings for $PA_{interested}$ on the PA factor and $NA_{distressed}$ on the NA factor were both fixed at 1 in order to scale the latent factors (equations 3a and 3c); the loadings for the remaining affect terms were estimated (e.g., equations 3b and 3d), and their product with the respective factor variance terms ($\xi_{PA}$ and $\xi_{NA}$), along with the residual terms (e.g., $\epsilon_{PAexcited}$ and $\epsilon_{NAafraid}$) define the observed affect items. Once again,
significant loadings and good fit indices were used to evaluate the fit of the measurement models and their appropriateness for use in the structural models.

3.2.2. Structural Models

Structural models were fitted in the following sequence: 1) Health Bias model, which omits all interaction effects; 2) PA moderation model, 3) NA moderation model, and 4) Combined moderation model, which includes the interaction effects for both NA and PA. Although the initial structural model is straightforward, modeling the latent interaction effects of the moderation models is complex, and requires the use of specification and/or estimation techniques that are not necessary for more basic latent models. The *Latent Moderated Structural Equations* (LMS) approach, developed by Klein and Moosbrugger (2000), accounts for the non-normal distributions present in latent interaction models by deriving a finite mixture of population-level multivariate normal distributions based on the conditional probabilities present in the observed data. These mixture densities are then used to estimate model parameters via the expectation maximization, or EM, algorithm, which is an iterative maximum-likelihood estimator. Briefly, the EM algorithm as applied in the LMS approach estimates values of the unobserved latent interaction effect using a log-likelihood function for the incomplete data (i.e., missing the interaction effect), based on the conditional probabilities derived from the mixture densities (this is the estimation step); next, the maximation step calculates the log-likelihood based on the data resulting from the estimation step. This process continues iteratively (E-step, then M-step, then E-step, etc.) until the value of the log-likelihood achieved in the M-step is maximized; the values used for the last iteration
of the EM algorithm are then used as the estimates for the model (Klein & Moosbrugger, 2000; Moosbrugger et al., 1997).

There are a few important differences between the LMS approach and the more traditional SEM approach to estimating latent interaction effects: first, whereas the traditional method analyzes covariance structures, the mixture density and conditional probability requirements of the LMS method require the use of the raw data; second, whereas the traditional approach estimates the interaction effect as its own latent variable—with indicators, mean, and variance parameters—the LMS approach only estimates the beta value reflecting the effect of the interaction between the two latent variables on the dependent factor, and does not estimate it as a latent factor itself. This results in a model that is more straightforward and parsimonious than the one that would result from the traditional approach; and although the mixture component of the LMS approach is more analytically complex than the more traditional approaches, it has been shown to work well with smaller samples (Moosbrugger et al., 1997), and has also been incorporated into software programs designed for SEM analysis (MPlus; Muthen & Muthen, 1998-2010), making it feasible and appropriate for the present purpose.

*Health Bias Model.* The first structural model to be tested examined the extent to which an individual’s perceptions of his or her health reflect his or her objective health indicators. The Objective Health factor was modeled as a predictor of the Perceived Health factor, with the path coefficient reflecting the impact of one’s objective health (as measured here) on his or her perceived health. The equation for this model is as follows:

\[
\eta_{PH} = \beta_1 \xi_{OH} + \delta_{PH}
\]  

(4)
The beta coefficient ($b_1$) is the primary parameter of interest here, as it represents the impact of Objective Health on Perceived Health; a significant path in the positive direction would indicate that the worse one’s health is—as indicated by the objective health measures—the worse their perception of their health is. The moderation models to follow were compared to this model as a baseline, so that the contribution of the interaction effects could be assessed (Muthen, 2012).

*Moderator Models.* In order to get a more complete picture of the affect-moderating effects on the observed health–perceived health relationship, the moderating functions of PA and NA were tested separately, followed by the final model, which included both interaction effects simultaneously. The structural equations for the PA and NA Moderator Models are shown below:

$$\eta_{PH} = \beta_1 \xi_{OH} + \beta_{2a} \xi_{PA} + \beta_{3a} \xi_{OH} \times \xi_{PA} + \delta_{PH} \quad (5a)$$

$$\eta_{PH} = \beta_1 \xi_{OH} + \beta_{2b} \xi_{NA} + \beta_{3b} \xi_{OH} \times \xi_{NA} + \delta_{PH} \quad (6a)$$

In both models, the latent Perceived Health factor is predicted by $\beta_1$, which represents the effect of the Objective Health Factor; $\beta_2$, which represents the effect of PA($\beta_{2a}$) or NA ($\beta_{2b}$); $\beta_3$, which represents the effect of the latent interaction between Objective Health and affect; and $\delta_{PH}$, which is the error not explained by the model. As mentioned before, the only parameter estimated for the interaction is $\beta_3$ here, and it is thus the parameter of greatest interest when it comes to the question of affect-related health bias at the global

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2 Note that the latent variable PH is now represented using a ($\eta$) symbol instead of the ($\xi$) symbol; this is simply to differentiate between endogenous (dependent) versus exogenous (independent or predictor) variables. The use of the ($\delta$) in the error (or disturbance) term rather than the ($\varepsilon$) used in the measurement models serves a similar purpose of differentiation, although in this case it is to make errors of latent variables distinct from those of manifest variables.
level. The formulas below present the same equations in an alternative form in order to aid in explanation (Muthen, 2012):

\[
\eta_{PH} = (\beta_1 + \beta_3 \xi_{PA}) \xi_{OH} + \beta_{2a} \xi_{PA} + \delta_{PH} \tag{5b}
\]

\[
\eta_{PH} = (\beta_1 + \beta_3 \xi_{NA}) \xi_{OH} + \beta_{2b} \xi_{NA} + \delta_{PH} \tag{6b}
\]

Here, it becomes more apparent that the extent to which \(\xi_{OH}\) influences \(\eta_{PH}\) is dependent on the affect moderating functions \((\beta_1 + \beta_3 \xi_{PA})\) and \((\beta_1 + \beta_3 \xi_{NA})\). A covariance parameter was also modeled in each case to capture the relationship between affect and objective health.

Because observed PA and NA scales tend to be moderately correlated, it was important to test a final model in which both affects—and their moderating functions—were modeled simultaneously. The structural equation for this model is shown below, in both standard (7a) and alternative (7b) forms:

\[
\eta_{PH} = \beta_1 \xi_{OH} + \beta_{2a} \xi_{PA} + \beta_{2b} \xi_{NA} + \beta_{3a} \xi_{OH} \times \xi_{PA} + \beta_{3b} \xi_{OH} \times \xi_{NA} + \delta_{PH} \tag{7a}
\]

\[
\eta_{PH} = (\beta_1 + \beta_{3a} \xi_{PA}) \xi_{OH} + (\beta_1 + \beta_{3b} \xi_{NA}) \xi_{OH} + \beta_{2a} \xi_{PA} + \beta_{2b} \xi_{NA} + \delta_{PH} \tag{7b}
\]

The resulting model is more complex than the previous models, with two interaction parameters being fit; three additional factor covariances—PA/NA, PA/OH, NA/OH—were also estimated.

In order to get at the state (or day) vs. trait affect question, the person-level parameter estimates for the day-level individual interaction effects were output and included as an additional (manifest) covariate on the latent Perceived Health factor, as shown in the formulas below:

\[
\eta_{PH} = \beta_1 \xi_{OH} + \beta_{2a} \xi_{PA} + \beta_{3a} \xi_{OH} \times \xi_{PA} + \beta_{4a}(DailyMod_{PA}) + \delta_{PH} \tag{19a}
\]

\[
\eta_{PH} = \beta_1 \xi_{OH} + \beta_{2b} \xi_{NA} + \beta_{3b} \xi_{OH} \times \xi_{NA} + \beta_{4b}(DailyMod_{NA}) + \delta_{PH} \tag{19b}
\]
Here, perceived health is predicted by objective health ($\beta_1 \xi_{OH}$), PA or NA ($\beta_{2a} \xi_{PA}$ and $\beta_{2b} \xi_{NA}$), their latent interaction effect ($\beta_{3a} \xi_{OH} \times \xi_{PA}$ and $\beta_{3b} \xi_{OH} \times \xi_{NA}$), and the day-level interaction effect obtained from the MLM analyses, $\beta_{4a}(\text{DailyMod}_{PA})$ and $\beta_{4b}(\text{DailyMod}_{NA})$, along with the disturbance term ($\delta_{PH}$). A combined model also tested the affect effects simultaneously as was done for the initial structural models (7a); a covariance parameter accounted for the possible correlation between PA and NA interaction effects:

$$\eta_{PH} = \beta_1 \xi_{OH} + \beta_{2a} \xi_{PA} + \beta_{2b} \xi_{NA} + \beta_{3a} \xi_{OH} \times \xi_{PA} + \beta_{3b} \xi_{OH} \times \xi_{NA} +$$

$$\beta_{4a}(\text{DailyMod}_{PA}) + \beta_{4b}(\text{DailyMod}_{NA}) + \delta_{PH}$$

A substantial reduction in the strength of the latent interaction effect on Perceived Health ($\beta_{3a}$ or $\beta_{3b}$), along with a significant effect for the added daily interaction predictor, would indicate that the affect-related health bias observed on the global level was largely a factor of daily-level affect processes. If the latent interaction effect retains its strength and significance, and the effect of the daily interaction variable is not significant, then it would indicate that the affect bias processes observed at the global level are indeed a factor of trait-level processes; and if both effects are similarly significant, then it would indicate that the daily affect bias is largely a factor of the trait-level processes present on the global level.

3.3 Analysis 2: Daily Health Bias

Multilevel modeling was used to test the daily level health bias hypotheses, permitting the analysis of day-level effects both within and across individuals. All daily predictor variables (daily health events, daily NA and PA) were centered at the person.
mean in order to aid in interpretation; all direct and interaction effects were treated as
random (i.e., allowed to vary from person to person). Mean terms for each daily variable
were also included as Level 2 effects on the intercept, in order to separate between- and
within-person effects. The sequence of models testing the daily health bias hypotheses
are presented next, with Level 1 (within-person) and Level 2 (between-person) effects
presented separately; random parameters are indicated by a $j$ subscript. The unconditional
baseline model, which contains no predictors, was tested first:

$$HlthSat_{ij} = \beta_{0j} + e_{ij} \quad (8a)$$
$$\beta_{0j} = \gamma_{00} + u_{0j} \quad (8b)$$

Here, $HlthSat_{ij}$ is the observed health satisfaction rating on day $i$ for person $j$; the $\beta_{0j}$ term
reflects the mean health satisfaction across days for person $j$, determined by $\gamma_{00}$ (the
overall grand mean of health satisfaction across participants) and $u_{0j}$ (the unique
contribution of person $j$ to his or her mean health satisfaction over and above the grand
mean). The $e_{ij}$ term is the residual variance in health satisfaction for day $i$ and person $j$ yet
to be accounted for.

The next model tested was an unconditional slope model, because although there
is no reason to expect there to be a systematic slope present in health satisfaction across
days, it is important to control for it in subsequent models if it does exist:

$$HlthSat_{ij} = \beta_{0j} + \beta_1(Day) + e_{ij} \quad (9a)$$
$$\beta_{0j} = \gamma_{00} + u_{0j} \quad (9b)$$
$$\beta_1 = \gamma_{DAY} + u_{1j} \quad (9c)$$

Here, an additional parameter is added to the previous model ($\beta_1$), representing the
contribution of the mean slope across participants on an individual’s slope ($\gamma_{DAY}$), and the
unique contribution of the individual to his or her slope across days ($u_{1j}$). Because the
\( \gamma_{DAY} \) slope parameter was not expected to be significant, these terms are not included in the models to follow.

Next in the sequence of models were tests of the individual direct effects of health events and daily affect on health satisfaction, the formulas for which are below:

\[
\text{HlthSat}_{ij} = \beta_{0j} + \beta_{2j} (HEV_{ij}) + e_{ij} \\
\beta_{0j} = \gamma_{00} + \gamma_{MHEV} (mHEV_{j}) + u_{0j} \\
\beta_{2j} = \gamma_{HEV} + u_{HEV_{j}} \\
\]

(10a)

(10b)

(10c)

\[
\text{HlthSat}_{ij} = \beta_{0j} + \beta_{3j} (PA_{ij}) + e_{ij} \\
\beta_{0j} = \gamma_{00} + \gamma_{MPA} (mPA_{j}) + u_{0j} \\
\beta_{3j} = \gamma_{PA} + u_{PA_{j}} \\
\]

(11a)

(11b)

(11c)

\[
\text{HlthSat}_{ij} = \beta_{0j} + \beta_{4j} (NA_{ij}) + e_{ij} \\
\beta_{0j} = \gamma_{00} + \gamma_{MNA} (mNA_{j}) + u_{0j} \\
\beta_{4j} = \gamma_{NA} + u_{NA_{j}} \\
\]

(12a)

(12b)

(12c)

Note the additional term on the intercept in each model (\( \gamma_{MHEV} \), \( \gamma_{MPA} \), and \( \gamma_{MNA} \)), which represent the Level 2 effects of an individual’s mean across days for each of the respective variables on the intercept. The terms \( \gamma_{HEV} \), \( \gamma_{PA} \), and \( \gamma_{NA} \) represent the fixed effects of each of the dependent variables on the health satisfaction for person \( j \) on day \( i \), whereas the parameters \( u_{HEV_{j}} \), \( u_{PA_{j}} \), and \( u_{NA_{j}} \) reflect the random—or person-level—variance components.

The next step was to run models including the direct effects of both the independent variable (health events here) and the moderator (PA or NA), as shown below:

\[
\text{HlthSat}_{ij} = \beta_{0j} + \beta_{2j} (HEV_{ij}) + \beta_{3j} (PA_{ij}) + e_{ij} \\
\beta_{0j} = \gamma_{00} + \gamma_{MHEV} (mHEV_{j}) + \gamma_{MPA} (mPA_{j}) + u_{0j} \\
\beta_{2j} = \gamma_{HEV} + u_{HEV_{j}} \\
\beta_{3j} = \gamma_{PA} + u_{PA_{j}} \\
\]

(13a)

(13b)

(13c)

(13d)

\[
\text{HlthSat}_{ij} = \beta_{0j} + \beta_{2j} (HEV_{ij}) + \beta_{4j} (NA_{ij}) + e_{ij} \\
\beta_{0j} = \gamma_{00} + \gamma_{MHEV} (mHEV_{j}) + \gamma_{MNA} (mNA_{j}) + u_{0j} \\
\]

(14a)

(14b)
\[ \beta_{2j} = \gamma_{HEV} + u_{HEVj} \quad (14c) \]
\[ \beta_{4j} = \gamma_{NA} + u_{NAj} \quad (14d) \]

The estimates from these direct effects models were then the basis for comparison for the estimates from the individual moderation models:

\[
\begin{align*}
\text{HlthSat}_{ij} & = \beta_{0j} + \beta_{2j} (\text{HEV}_{ij}) + \beta_{3j} (\text{PA}_{ij}) + \beta_{5j} (\text{HEVxPA}_{ij}) + e_{ij} \\
\beta_{0j} & = \gamma_{00} + \gamma_{MHEV} (m\text{HEV}_{j}) + \gamma_{MPA} (m\text{PA}_{j}) + u_{0j} \\
\beta_{2j} & = \gamma_{HEV} + u_{HEVj} \\
\beta_{3j} & = \gamma_{PA} + u_{PAj} \\
\beta_{5j} & = \gamma_{HEVPA} + u_{HEVPAj} \\
\end{align*}
\]

(15a)

\[
\begin{align*}
\text{HlthSat}_{ij} & = \beta_{0j} + \beta_{4j} (\text{NA}_{ij}) + \beta_{6j} (\text{HEVxNA}_{ij}) + e_{ij} \\
\beta_{0j} & = \gamma_{00} + \gamma_{MHEV} (m\text{HEV}_{j}) + \gamma_{MNA} (m\text{NA}_{j}) + u_{0j} \\
\beta_{4j} & = \gamma_{NA} + u_{NAj} \\
\beta_{6j} & = \gamma_{HEVNA} + u_{HEVNAj} \\
\end{align*}
\]

(16a)

Here, the primary interest is in the moderation parameters; \( \gamma_{HEVNA} \) and \( \gamma_{HEVPA} \) reflect the fixed moderation effects, and \( u_{HEVNAj} \) and \( u_{HEVPAj} \) represent the respective random (variance) effects. As PA and NA tend to be moderately correlated with one another, it was important to ascertain the unique contribution of each affect and its associated moderating function; this was done using the following two models, and comparing them much like the individual direct effects and interaction models shown above:

\[
\begin{align*}
\text{HlthSat}_{ij} & = \beta_{0j} + \beta_{2j} (\text{HEV}_{ij}) + \beta_{3j} (\text{PA}_{ij}) + \beta_{4j} (\text{NA}_{ij}) + e_{ij} \\
\beta_{0j} & = \gamma_{00} + \gamma_{MHEV} (m\text{HEV}_{j}) + \gamma_{MPA} (m\text{PA}_{j}) + \gamma_{MNA} (m\text{NA}_{j}) + u_{0j} \\
\beta_{2j} & = \gamma_{HEV} + u_{HEVj} \\
\beta_{3j} & = \gamma_{PA} + u_{PAj} \\
\beta_{4j} & = \gamma_{NA} + u_{NAj} \\
\beta_{6j} & = \gamma_{HEVxPA} + u_{HEVxPAj} \\
\end{align*}
\]

(17a)

\[
\begin{align*}
\text{HlthSat}_{ij} & = \beta_{0j} + \beta_{2j} (\text{HEV}_{ij}) + \beta_{3j} (\text{PA}_{ij}) + \beta_{4j} (\text{NA}_{ij}) + \beta_{5j} (\text{HEVxPA}_{ij}) + \beta_{6j} (\text{HEVxNA}_{ij}) + e_{ij} \\
\beta_{0j} & = \gamma_{00} + \gamma_{MHEV} (m\text{HEV}_{j}) + \gamma_{MPA} (m\text{PA}_{j}) + \gamma_{MNA} (m\text{NA}_{j}) + u_{0j} \\
\beta_{2j} & = \gamma_{HEV} + u_{HEVj} \\
\beta_{3j} & = \gamma_{PA} + u_{PAj} \\
\beta_{4j} & = \gamma_{NA} + u_{NAj} \\
\beta_{5j} & = \gamma_{HEVxPA} + u_{HEVxPAj} \\
\beta_{6j} & = \gamma_{HEVxNA} + u_{HEVxNAj} \\
\end{align*}
\]

(18a)
These models were also compared with the individual versions (i.e., compare Model 11 with Models 8 and 9) in order to get at the unique effects of each affect moderation term.

Finally, in order to test for the competing effects of global- vs. day-level affect on daily health bias, observed scale scores for global positive and negative affect were computed and terms for both direct and indirect effects were used as additional predictors in the daily interaction models (21, 22, and 23), as shown in Figures 13 and 14, and the formulas below:

\[ H_{i,j} = \beta_{0j} + \beta_{2j}(HEV_{ij}) + \beta_{3j}(PA_{ij}) + \beta_{5j}(HEVxPA_{ij}) + \beta_{7j}(HEVxPA_{trait}ij) \]

\[ \begin{align*}
\beta_{0j} &= \gamma_{00} + \gamma_{\text{MHEV}}(mHEV_{j}) + \gamma_{\text{MPA}}(mPA_{j}) + \gamma_{\text{PAtrait}}(PA_{trait}) + u_{0j} \\
\beta_{2j} &= \gamma_{\text{HEV}} + u_{\text{HEV}j} \\
\beta_{3j} &= \gamma_{\text{PA}} + u_{\text{PA}j} \\
\beta_{5j} &= \gamma_{\text{HEV}\times\text{PA}} + u_{\text{HEV}\times\text{PA}j} \\
\beta_{7j} &= \gamma_{\text{HEV}\times\text{PAtrait}} + u_{\text{HEV}\times\text{PAtrait}j} 
\end{align*} \]

\[ (21a) \]

\[ H_{i,j} = \beta_{0j} + \beta_{2j}(HEV_{ij}) + \beta_{4j}(NA_{ij}) + \beta_{6j}(HEVxNA_{ij}) + \beta_{8j}(HEVxNA_{trait}ij) \]

\[ \begin{align*}
\beta_{0j} &= \gamma_{00} + \gamma_{\text{MHEV}}(mHEV_{j}) + \gamma_{\text{MNA}}(mNA_{j}) + \gamma_{\text{NAtrait}}(NA_{trait}) + u_{0j} \\
\beta_{2j} &= \gamma_{\text{HEV}} + u_{\text{HEV}j} \\
\beta_{4j} &= \gamma_{\text{NA}} + u_{\text{NA}j} \\
\beta_{6j} &= \gamma_{\text{HEV}\times\text{NA}} + u_{\text{HEV}\times\text{NA}j} \\
\beta_{8j} &= \gamma_{\text{HEV}\times\text{NAtrait}} + u_{\text{HEV}\times\text{NAtrait}j} 
\end{align*} \]

\[ (22a) \]

\[ H_{i,j} = \beta_{0j} + \beta_{2j}(HEV_{ij}) + \beta_{4j}(NA_{ij}) + \beta_{6j}(HEVxNA_{ij}) + \beta_{7j}(HEVxPA_{trait}ij) + \beta_{8j}(HEVxNA_{trait}ij) + e_{ij} \]

\[ \begin{align*}
\beta_{0j} &= \gamma_{00} + \gamma_{\text{MHEV}}(mHEV_{j}) + \gamma_{\text{MPA}}(mPA_{j}) + \gamma_{\text{MNA}}(mNA_{j}) + \gamma_{\text{PAtrait}}(PA_{trait}) + \gamma_{\text{NAtrait}}(NA_{trait}) + u_{0j} \\
\beta_{2j} &= \gamma_{\text{HEV}} + u_{\text{HEV}j} \\
\beta_{4j} &= \gamma_{\text{NA}} + u_{\text{NA}j} \\
\beta_{6j} &= \gamma_{\text{HEV}\times\text{NA}} + u_{\text{HEV}\times\text{NA}j} \\
\beta_{7j} &= \gamma_{\text{HEV}\times\text{PAtrait}} + u_{\text{HEV}\times\text{PAtrait}j} \\
\beta_{8j} &= \gamma_{\text{HEV}\times\text{NAtrait}} + u_{\text{HEV}\times\text{NAtrait}j} 
\end{align*} \]

\[ (23a) \]
As was done on the global level, the estimates for the day-level interaction effects obtained by these models were compared with those from the models without the trait affect terms (models 15, 16, and 18) in order to assess the extent to which the day-level health bias effects are primarily a factor of trait- or daily-level affect processes.
CHAPTER 4:

RESULTS

4.1 Descriptive Statistics

4.1.1 Global Variables

The means, standard deviations, and correlations of the variables used in the global-level analyses are shown in Table 1. All significant correlations are in the expected directions; importantly, all of the variables intended to indicate a given factor correlate significantly with one another (e.g., the Metabolic, Lipid, Pressure, and Diagnosis variables—all manifest indicators of the global Objective Health factor—are significantly related to each other). The two daily bias parameters—reflecting the parameter estimates for health bias across days for each individual—were significantly correlated ($r = -0.48$, $p < .001$). The highest correlation among predictor variables was for a) the relationship between the somatic health variable and the overall perceived health rating ($r = 0.50$, $p < .001$); and b) the association between the Big 5 Diagnosis variable and the Metabolic composite variable ($r = 0.50$, $p < .001$). Age is positively correlated with the Diagnosis variable ($p < .05$) and the Somatic Health variable ($p < .01$)

4.1.2 Daily Variables

Tables 2 and 3 show the means, standard deviations, and correlations for the variables included in the day-level models. Concerning the correlations among the day-
Table 1

Descriptive Statistics of the Global Level Variables (N = 153)

<table>
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<tr>
<th></th>
<th>Mean*</th>
<th>SD*</th>
<th>1</th>
<th>2</th>
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<th>4</th>
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<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
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<tr>
<td>1. zMetab</td>
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<td>5. zOverall</td>
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<td>.09</td>
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<td>.18</td>
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<td>9. GlblPA</td>
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<td>-.10</td>
<td>-.10</td>
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<td>.07</td>
<td>-.22</td>
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<td>.02</td>
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<td>.09</td>
<td>.09</td>
<td>-.07</td>
<td>.22</td>
<td>.04</td>
<td>.02</td>
<td>.05</td>
<td>-.02</td>
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</table>

Note: p < .05 in *italics*; p < .01 in **bold italics**; p < .001 in **bold**. Means and SD’s of standardized variables are in their unstandardized form. Rather than presenting the individual affect item correlations, the combined affect terms are used here to establish the degree of correlation between affect and the other variables.
level variables (daily health events, daily PA, daily NA, and daily health satisfaction), all were significantly associated with one another in the expected directions (Table 2); the highest correlation was that between PA and NA on the day level ($r = -0.27, p < .001$). Daily PA was most correlated with the dependent variable health satisfaction ($r = 0.20, p < .001$).

Table 3 shows the correlations among all terms included in the daily model, both Level 1 (the day-level variables) and Level 2 (the mean terms, the global affect variables, and age). Correlations reflect the data on Day 1, as reporting coefficients derived from all 8512 observations (56 days x 152 participants) would artificially inflate significance values. As would be expected, the highest correlations are between the terms reflecting more stable affect characteristics: the mean daily PA term with the global PA term ($r = 0.71, p < .001$); and the mean daily NA term with the global NA term ($r = 0.74, p < .001$). Other significant day-level correlations of note include that between daily PA and mean...
TABLE 3

DESCRIPTIVE STATISTICS OF THE DAY LEVEL VARIABLES

(DAY = 1)

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<th>SD</th>
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<th>cEvent</th>
<th>mDlyPA</th>
<th>cDlyPA</th>
<th>GlblPA</th>
<th>mDlyNA</th>
<th>cDlyNA</th>
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</tr>
<tr>
<td>cEvent</td>
<td>0.03</td>
<td>0.81</td>
<td>-.20</td>
<td>-.20</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mDlyPA</td>
<td>45.72</td>
<td>8.95</td>
<td>-.17</td>
<td>.06</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cDlyPA</td>
<td>0.20</td>
<td>6.85</td>
<td>.08</td>
<td>.12</td>
<td>-.06</td>
<td>.44</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GlblPA</td>
<td>49.09</td>
<td>7.53</td>
<td>-.13</td>
<td>.05</td>
<td>.71</td>
<td>-.14</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mDlyNA</td>
<td>13.67</td>
<td>4.70</td>
<td>-.14</td>
<td>-.003</td>
<td>.01</td>
<td>-.16</td>
<td>.15</td>
<td>-.07</td>
<td>--</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cDlyNA</td>
<td>1.27</td>
<td>4.31</td>
<td>-.06</td>
<td>-.05</td>
<td>.04</td>
<td>-.03</td>
<td>-.27</td>
<td>-.16</td>
<td>-.03</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>GlblNA</td>
<td>16.37</td>
<td>5.91</td>
<td>-.16</td>
<td>-.01</td>
<td>.07</td>
<td>-.24</td>
<td>.08</td>
<td>-.25</td>
<td>.74</td>
<td>.18</td>
<td>--</td>
</tr>
<tr>
<td>Age</td>
<td>71.20</td>
<td>4.89</td>
<td>.22</td>
<td>.01</td>
<td>-.02</td>
<td>.01</td>
<td>.01</td>
<td>.02</td>
<td>.03</td>
<td>-.11</td>
<td>-.07</td>
</tr>
</tbody>
</table>

NOTE: p < .05 in italics; p < .01 in bold italics; p < .001 in bold.
daily PA ($r = 0.44, p < .001$), whereas that between daily NA and mean daily NA was not significant. The terms for mean daily PA and global PA have the strongest correlation with the dependent variable, health satisfaction ($r = 0.30, p < .001$).

4.2 Preliminary Analyses

4.2.1 Affect scales

*Global Affect Analysis.* Both 2- and 3-factor exploratory factor analyses were used to confirm the structure of global affect: information from the scree plot—which plots each factor according to the amount of variance explained (eigenvalues), with the ideal number of factors represented by the last number before the “elbow” of the plot—and eigenvalues reveal that a 2-factor solution is the best fit for the global affect data (only the first two eigenvalues were above the elbow of the scree plot and greater than 1.0). The first column of Table 4 shows the rotated factor solution for the final 2-factor treatment of global affect. Note that *fatigued* failed to load above 0.3 on any factor, resulting in it being dropped from the analysis. Additionally, because the *guilty* and *ashamed* items loaded on their own factor (Factor 3) in the 3-factor solution, confirmatory factor analysis (CFA) was used to compare model fit for the 2-factor models with and without the guilt/shame items on the global level; the first row of Table 5 shows the results of this comparison. Thus, the 2-factor PA/NA solution omitting guilt and shame emerged as the best fit for the global data (CFI = 0.927; RMSEA = 0.065).

*Daily Affect Analysis.* In order to confirm structure of affect across days, a random number generator was used to select 10 random days of daily affect data (1, 9, 15, 19, 23, 36, 44, 47, 51, 56) on which to run the EFA’s. According to the scree plot on
TABLE 4

ROTATED 2-FACTOR SOLUTIONS FOR GLOBAL- AND DAY-LEVEL AFFECT DATA

<table>
<thead>
<tr>
<th>Affect Item</th>
<th>Global</th>
<th>Day 1</th>
<th>Day 9</th>
<th>Day 15</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PA</td>
<td>NA</td>
<td>PA</td>
<td>NA</td>
</tr>
<tr>
<td>Active</td>
<td>0.553</td>
<td></td>
<td>0.677</td>
<td></td>
</tr>
<tr>
<td>Enthusiastic</td>
<td>0.693</td>
<td></td>
<td>0.748</td>
<td></td>
</tr>
<tr>
<td>Attentive</td>
<td>0.574</td>
<td></td>
<td>0.687</td>
<td></td>
</tr>
<tr>
<td>Excited</td>
<td>0.740</td>
<td></td>
<td>0.676</td>
<td></td>
</tr>
<tr>
<td>Determined</td>
<td>0.741</td>
<td></td>
<td>0.721</td>
<td></td>
</tr>
<tr>
<td>Relaxed</td>
<td>0.440</td>
<td></td>
<td>0.414</td>
<td></td>
</tr>
<tr>
<td>Cheerful</td>
<td>0.738</td>
<td></td>
<td>0.675</td>
<td></td>
</tr>
<tr>
<td>Strong</td>
<td>0.757</td>
<td></td>
<td>0.607</td>
<td></td>
</tr>
<tr>
<td>Inspired</td>
<td>0.754</td>
<td></td>
<td>0.749</td>
<td></td>
</tr>
<tr>
<td>Interested</td>
<td>0.824</td>
<td></td>
<td>0.769</td>
<td></td>
</tr>
<tr>
<td>Alert</td>
<td>0.695</td>
<td></td>
<td>0.753</td>
<td></td>
</tr>
<tr>
<td>Proud</td>
<td>0.619</td>
<td></td>
<td>0.522</td>
<td></td>
</tr>
<tr>
<td>Self-Assured</td>
<td>0.642</td>
<td></td>
<td>0.722</td>
<td></td>
</tr>
<tr>
<td>Afraid</td>
<td>0.740</td>
<td></td>
<td>0.780</td>
<td></td>
</tr>
<tr>
<td>Hostile</td>
<td>0.548</td>
<td></td>
<td>0.452</td>
<td></td>
</tr>
<tr>
<td>Worried</td>
<td>0.751</td>
<td></td>
<td>0.771</td>
<td></td>
</tr>
<tr>
<td>Scared</td>
<td>0.777</td>
<td></td>
<td>0.871</td>
<td></td>
</tr>
<tr>
<td>Distressed</td>
<td>0.834</td>
<td></td>
<td>0.818</td>
<td></td>
</tr>
<tr>
<td>Nervous</td>
<td>0.828</td>
<td></td>
<td>0.867</td>
<td></td>
</tr>
<tr>
<td>Upset</td>
<td>0.778</td>
<td></td>
<td>0.909</td>
<td></td>
</tr>
<tr>
<td>Irritable</td>
<td>0.680</td>
<td></td>
<td>0.427</td>
<td></td>
</tr>
<tr>
<td>Jittery</td>
<td>0.740</td>
<td></td>
<td>0.695</td>
<td></td>
</tr>
<tr>
<td>Depressed</td>
<td>0.781</td>
<td></td>
<td>0.793</td>
<td></td>
</tr>
<tr>
<td>Miserable</td>
<td>0.719</td>
<td></td>
<td>0.771</td>
<td></td>
</tr>
</tbody>
</table>

| Eigenvalue    | 4.98 (34%) | 7.44 (51%) | 5.06 (33%) | 7.62 (49%) | 5.27 (30%) | 10.06 (58%) | 8.64 (50%) | 5.88 (34%) |

NOTE: Day 1 was generally Sunday, meaning that Day 9 was a Monday, and Day 15 was a Saturday for most participants.
TABLE 5

MODEL FIT INDICES FOR CFA MODEL COMPARISONS ON AFFECT DATA

<table>
<thead>
<tr>
<th>MODEL</th>
<th>Par.</th>
<th>DF</th>
<th>Chi-Square</th>
<th>CFI</th>
<th>RMSEA</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Factor, w/Guilt</td>
<td>60</td>
<td>291</td>
<td>487.92***</td>
<td>.907</td>
<td>.071</td>
<td>607.92</td>
<td>783.12</td>
</tr>
<tr>
<td>2-Factor, no Guilt</td>
<td>55</td>
<td>245</td>
<td>386.05***</td>
<td>.927</td>
<td>.065</td>
<td>496.05</td>
<td>656.65</td>
</tr>
<tr>
<td>Day 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Factor, w/Guilt</td>
<td>60</td>
<td>291</td>
<td>682.64***</td>
<td>.834</td>
<td>.098</td>
<td>802.64</td>
<td>979.13</td>
</tr>
<tr>
<td>2-Factor, no Guilt</td>
<td>55</td>
<td>245</td>
<td>540.33***</td>
<td>.860</td>
<td>.093</td>
<td>650.33</td>
<td>812.12</td>
</tr>
<tr>
<td>Day 9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Factor, w/Guilt</td>
<td>60</td>
<td>291</td>
<td>708.40***</td>
<td>.870</td>
<td>.104</td>
<td>828.40</td>
<td>1002.27</td>
</tr>
<tr>
<td>2-Factor, no Guilt</td>
<td>55</td>
<td>245</td>
<td>541.43***</td>
<td>.897</td>
<td>.095</td>
<td>651.43</td>
<td>810.81</td>
</tr>
<tr>
<td>Day 15</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Factor, w/Guilt</td>
<td>60</td>
<td>291</td>
<td>703.54***</td>
<td>.853</td>
<td>.102</td>
<td>823.54</td>
<td>999.18</td>
</tr>
<tr>
<td>2-Factor, no Guilt</td>
<td>55</td>
<td>245</td>
<td>608.02***</td>
<td>.862</td>
<td>.104</td>
<td>718.02</td>
<td>879.02</td>
</tr>
</tbody>
</table>

NOTE: All factor loadings and covariances were significant in all models.

each of these days (see Figure 1 for an example) and the corresponding eigenvalues, (only the first two factors had eigenvalues above 1.0), the affect data was best represented by 2 factors: Positive Affect (PA) and Negative Affect (NA). As was done on the global level, in initial exploration, EFA’s were run on each day specifying both 2- and 3-factor solutions; overall, due to the inconsistency of the 3-factor solution across days, the 2-factor solution was retained as the best representation of the day-level data. Because it failed to load on either factor on four days, the fatigued item was dropped from the NA factor; the satisfied item was also omitted due to its conceptual similarity to the dependent variable, health satisfaction. Additionally, as was the case on the global level,
Figure 1. Example scree plot of eigenvalues from the EFA on the day-level affect data (Day = 19).
the items *guilty* and *ashamed* consistently loaded on their own factor in the 3-factor solution; CFA analyses compared the fit of models with and without these items, and results consistently revealed the 2-factor solution without the guilt/shame items to fit better, which led to these items being dropped from the NA factor (see Table 5). Table 4 shows the rotated 2-factor solutions on the first three randomly-selected days (1, 9, 15) for the final set of affect items. Confirmatory Factor Analysis (Table 5) revealed acceptable fit for the final 2-factor solution across days: the CFI ranged from 0.836 (Day 56) to 0.942 (Day 19), with a mean of 0.887 across the ten randomly-selected days; the RMSEA ranged from 0.069 (Day 19) to 0.111 (Day 56), with a mean of 0.093 across the ten days.

4.2.2 Physiological Composite Variables

Initially, EFA was used to examine the factor structure of all 13 physical/physiological indicators (Body Mass Index, Waist/Hip Ratio, Hemoglobin a1c, Heart Rate, Systolic Blood Pressure, Diastolic Blood Pressure, HDL Cholesterol, HDL/Total Cholesterol Ratio, Triglycerides, Homocysteine, Interleukin-6, DHEAS, and C-Reactive Protein). Looking at the scree plot (Figure 2), it appears that the “elbow” of the curve begins at the fourth factor, indicating that the physiological data are best represented by a 3-factor structure. The output of the initial 3-factor EFA (shown in Table 6) also indicates a clean 3-factor item clustering, at least for the indicators of metabolic and cardiovascular function. Thus, despite the fact that the eigenvalue of the 3rd factor is < 1.0 (0.66), the three-factor structure will be used to create the composite variables that will serve as manifest indicators in the SEM analysis. Unfortunately, the indicators of immune function (IL-6, CRP, DHEAS) did not sufficiently load on any
Figure 2. Scree plot from the EFA on the physiological indicators.
results for 3-factor efa on physiological indicators

<table>
<thead>
<tr>
<th></th>
<th>Factor 1 CV_Lipids</th>
<th>Factor 2 CV_Pressure</th>
<th>Factor 3 Metabolic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cholesterol Ratio</td>
<td>0.891</td>
<td>0.079</td>
<td>-0.085</td>
</tr>
<tr>
<td>Triglycerides</td>
<td>0.775</td>
<td>-0.015</td>
<td>-0.105</td>
</tr>
<tr>
<td>HDL</td>
<td>0.643</td>
<td>-0.040</td>
<td>0.291</td>
</tr>
<tr>
<td>DBP</td>
<td>-0.003</td>
<td>0.821</td>
<td>-0.030</td>
</tr>
<tr>
<td>SBP</td>
<td>-0.044</td>
<td>0.755</td>
<td>0.070</td>
</tr>
<tr>
<td>Heart Rate</td>
<td>0.096</td>
<td>0.271</td>
<td>0.049</td>
</tr>
<tr>
<td>Hemoglobin a1c</td>
<td>-0.011</td>
<td>-0.018</td>
<td>0.564</td>
</tr>
<tr>
<td>Waist-Hip Ratio</td>
<td>0.208</td>
<td>-0.055</td>
<td>0.394</td>
</tr>
<tr>
<td>BMI</td>
<td>0.008</td>
<td>0.151</td>
<td>0.380</td>
</tr>
<tr>
<td>Homocysteine</td>
<td>-0.088</td>
<td>-0.178</td>
<td>0.345</td>
</tr>
<tr>
<td>C-Reactive Protein</td>
<td>0.012</td>
<td>0.197</td>
<td>-0.038</td>
</tr>
<tr>
<td>Interleukin-6</td>
<td>-0.142</td>
<td>0.193</td>
<td>-0.058</td>
</tr>
<tr>
<td>DHEAS</td>
<td>0.022</td>
<td>0.124</td>
<td>-0.075</td>
</tr>
<tr>
<td><strong>Eigenvalue</strong></td>
<td>2.55 (60%)</td>
<td>1.05 (25%)</td>
<td>0.66 (15%)</td>
</tr>
</tbody>
</table>

factor, leading to their being dropped from the analysis. Homocysteine, despite its significant loading (.345) on the metabolic factor, was also dropped, as there is no theoretical or medical rationale for its inclusion on the metabolic factor (it is primarily an indicator of cardiovascular function, as well as immune function/inflammation). The final factor breakdown, confirmed via CFA (Table 7), was therefore as follows: the Metabolic Factor was comprised of waist/hip ratio, bmi, and a1c; the Lipid Domain Factor of Cardiovascular Function was comprised of HDL, cholesterol ratio, and triglycerides; and the Pressure Domain Factor of Cardiovascular Function was comprised of heart rate, SBP, and DBP.
### TABLE 7

**RESULTS FOR CFA ON PHYSIOLOGICAL INDICATORS**

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Estimate</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CV_Lipids Factor</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cholesterol Ratio</td>
<td>1.00</td>
<td>--</td>
</tr>
<tr>
<td>Triglycerides</td>
<td>0.695 (0.08)</td>
<td>0.000</td>
</tr>
<tr>
<td>HDL</td>
<td>0.657 (0.08)</td>
<td>0.000</td>
</tr>
<tr>
<td>CV_Pressure Factor</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DBP</td>
<td>1.00</td>
<td>--</td>
</tr>
<tr>
<td>SBP</td>
<td>0.790 (0.14)</td>
<td>0.000</td>
</tr>
<tr>
<td>Heart Rate</td>
<td>0.338 (0.09)</td>
<td>0.000</td>
</tr>
<tr>
<td>Metabolic Factor</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hemoglobin a1c</td>
<td>1.00</td>
<td>--</td>
</tr>
<tr>
<td>Waist-Hip Ratio</td>
<td>0.655 (0.25)</td>
<td>0.007</td>
</tr>
<tr>
<td>BMI</td>
<td>0.913 (0.39)</td>
<td>0.018</td>
</tr>
</tbody>
</table>

**Model Fit:**

\[ X^2(24) = 55.33, \; p = .0003 \]

\[ CFI = .92; \; RMSEA = .09 \]

4.3 Analysis 1: Global Health Bias

4.3.1 Measurement Models

The estimated factor loadings (standardized and unstandardized), standard error of the estimates, residual variances of the manifest variables, the variance of the latent factor, and the overall model fit for each of the four measurement models are shown in Table 8; Figures 3-5 illustrate these models.
<table>
<thead>
<tr>
<th>Measurement Model Estimates</th>
<th>Unstandardized</th>
<th>Standardized</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective Health $\rightarrow$ Metabolic</td>
<td>1.00</td>
<td>0.838</td>
<td>--</td>
</tr>
<tr>
<td>Objective Health $\rightarrow$ Lipids</td>
<td>0.479 (0.14)</td>
<td>0.403</td>
<td>0.000</td>
</tr>
<tr>
<td>Objective Health $\rightarrow$ Pressure</td>
<td>0.403 (0.14)</td>
<td>0.340</td>
<td>0.004</td>
</tr>
<tr>
<td>Objective Health $\rightarrow$ Diagnoses</td>
<td>0.700 (0.16)</td>
<td>0.591</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Metabolic</td>
<td>0.299 (0.16)</td>
<td>0.298</td>
<td>0.055</td>
</tr>
<tr>
<td>Residual Variance—Lipids</td>
<td>0.832 (0.10)</td>
<td>0.837</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Pressure</td>
<td>0.879 (0.11)</td>
<td>0.885</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Diagnoses</td>
<td>0.644 (0.10)</td>
<td>0.651</td>
<td>0.000</td>
</tr>
<tr>
<td>Variance—Objective Health</td>
<td>0.704 (0.19)</td>
<td>1.00</td>
<td>0.000</td>
</tr>
<tr>
<td>Perceived Health $\rightarrow$ Overall Rating</td>
<td>1.00</td>
<td>0.707</td>
<td>--</td>
</tr>
<tr>
<td>Perceived Health $\rightarrow$ Past Comparison</td>
<td>0.835 (0.15)</td>
<td>0.597</td>
<td>0.000</td>
</tr>
<tr>
<td>Perceived Health $\rightarrow$ Peer Comparison</td>
<td>0.643 (0.15)</td>
<td>0.461</td>
<td>0.000</td>
</tr>
<tr>
<td>Perceived Health $\rightarrow$ Somatic Health</td>
<td>0.993 (0.17)</td>
<td>0.715</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Overall</td>
<td>0.512 (0.10)</td>
<td>0.501</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Past</td>
<td>0.718 (0.10)</td>
<td>0.787</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Peer</td>
<td>0.641 (0.09)</td>
<td>0.643</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Somatic</td>
<td>0.482 (0.10)</td>
<td>0.489</td>
<td>0.000</td>
</tr>
<tr>
<td>Variance—Perceived Health</td>
<td>0.510 (0.13)</td>
<td>1.00</td>
<td>0.000</td>
</tr>
<tr>
<td>PA $\rightarrow$ Interested</td>
<td>1.00</td>
<td>0.792</td>
<td>--</td>
</tr>
<tr>
<td>PA $\rightarrow$ Enthusiastic</td>
<td>0.878 (0.10)</td>
<td>0.694</td>
<td>0.000</td>
</tr>
<tr>
<td>PA $\rightarrow$ Attentive</td>
<td>0.755 (0.10)</td>
<td>0.592</td>
<td>0.000</td>
</tr>
<tr>
<td>PA $\rightarrow$ Excited</td>
<td>0.866 (0.10)</td>
<td>0.684</td>
<td>0.000</td>
</tr>
<tr>
<td>PA $\rightarrow$ Determined</td>
<td>0.948 (0.10)</td>
<td>0.751</td>
<td>0.000</td>
</tr>
<tr>
<td>PA $\rightarrow$ Relaxed</td>
<td>0.576 (0.10)</td>
<td>0.455</td>
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<tr>
<td>PA $\rightarrow$ Cheerful</td>
<td>0.916 (0.10)</td>
<td>0.724</td>
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<tr>
<td>PA $\rightarrow$ Strong</td>
<td>0.950 (0.10)</td>
<td>0.751</td>
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<tr>
<td>PA $\rightarrow$ Inspired</td>
<td>0.924 (0.08)</td>
<td>0.731</td>
<td>0.000</td>
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<tr>
<td>PA $\rightarrow$ Active</td>
<td>0.688 (0.10)</td>
<td>0.541</td>
<td>0.000</td>
</tr>
<tr>
<td>PA $\rightarrow$ Alert</td>
<td>0.893 (0.10)</td>
<td>0.708</td>
<td>0.000</td>
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<tr>
<td>PA $\rightarrow$ Proud</td>
<td>0.765 (0.10)</td>
<td>0.606</td>
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<tr>
<td>PA $\rightarrow$ Self-Assured</td>
<td>0.844 (0.10)</td>
<td>0.668</td>
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<tr>
<td>Residual Variance—Interested</td>
<td>0.370 (0.05)</td>
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<td>Residual Variance—Enthusiastic</td>
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<td>Residual Variance—Attentive</td>
<td>0.654 (0.08)</td>
<td>0.649</td>
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<tr>
<td>Residual Variance—Excited</td>
<td>0.531 (0.07)</td>
<td>0.532</td>
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TABLE 8 (contd.)

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<th>Standardized</th>
<th>p-value</th>
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<td>Residual Variance—Determined</td>
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<td>0.000</td>
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<td>Variance—Positive Affect</td>
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<tr>
<td>NA → Distressed</td>
<td>1.00</td>
<td>0.854</td>
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<tr>
<td>NA → Hostile</td>
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<td>NA → Upset</td>
<td>0.898 (0.08)</td>
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<tr>
<td>NA → Irritable</td>
<td>0.776 (0.09)</td>
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<tr>
<td>NA → Depressed</td>
<td>0.932 (0.08)</td>
<td>0.796</td>
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<tr>
<td>NA → Miserable</td>
<td>0.831 (0.08)</td>
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<tr>
<td>NA → Afraid</td>
<td>0.790 (0.09)</td>
<td>0.674</td>
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<tr>
<td>NA → Worried</td>
<td>0.900 (0.08)</td>
<td>0.767</td>
<td>0.000</td>
</tr>
<tr>
<td>NA → Scared</td>
<td>0.877 (0.08)</td>
<td>0.749</td>
<td>0.000</td>
</tr>
<tr>
<td>NA → Nervous</td>
<td>0.951 (0.08)</td>
<td>0.812</td>
<td>0.000</td>
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<tr>
<td>NA → Jittery</td>
<td>0.811 (0.09)</td>
<td>0.688</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Distressed</td>
<td>0.269 (0.04)</td>
<td>0.271</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Hostile</td>
<td>0.720 (0.08)</td>
<td>0.725</td>
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<tr>
<td>Residual Variance—Upset</td>
<td>0.410 (0.05)</td>
<td>0.413</td>
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<tr>
<td>Residual Variance—Irritable</td>
<td>0.554 (0.07)</td>
<td>0.561</td>
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<tr>
<td>Residual Variance—Depressed</td>
<td>0.363 (0.05)</td>
<td>0.367</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Miserable</td>
<td>0.493 (0.06)</td>
<td>0.498</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Afraid</td>
<td>0.542 (0.07)</td>
<td>0.546</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Worried</td>
<td>0.409 (0.05)</td>
<td>0.412</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Scared</td>
<td>0.436 (0.06)</td>
<td>0.440</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Nervous</td>
<td>0.338 (0.05)</td>
<td>0.341</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual Variance—Jittery</td>
<td>0.527 (0.07)</td>
<td>0.526</td>
<td>0.000</td>
</tr>
<tr>
<td>Variance—Negative Affect</td>
<td>0.722 (0.11)</td>
<td>1.00</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Measurement Model Fit
Objective Health Factor $X^2(2) = 7.22, p = .027; \text{CFI} = .93; \text{RMSEA} = .131$
Perceived Health Factor $X^2(2) = 2.82, p = .245; \text{CFI} = .99; \text{RMSEA} = .052$
PA Factor $X^2(61) = 118.78, p = .000; \text{CFI} = .94; \text{RMSEA} = .079$
NA Factor $X^2(41) = 63.51, p = .014; \text{CFI} = .98; \text{RMSEA} = .060$
Objective health. First, as can be seen in Table 8 (and Figure 3), all factor loadings (Lipid, Pressure, and Diagnosis variables) were significant for the latent Objective Health factor (note that the loading for the Metabolic variable was fixed to 1.0 in order to scale the factor); in terms of model fit, the RMSEA is somewhat higher than desired, but the $X^2$ and CFI indices are within acceptable ranges, indicating acceptable fit.

![Diagram](attachment:image.png)

Figure 3. Global Analyses: Objective Health Factor Measurement Model Results

Perceived health. Moving on to the measurement model for the latent factor of Perceived Health, we again see (Table 8; Figure 4) that all factor loadings (Past Comparison, Peer Comparison, Somatic Health) were significant, with the loading for the Overall Rating variable fixed to 1.0 to scale the factor. The fit indices demonstrate very good fit, as the $X^2$ is non-significant, the CFI is nearly 1.0, and the RMSEA is nearing .05.

Affect. Figure 5 shows the loadings for each affect item on the respective Positive and Negative Affect factor. Here, and in Table 8, we see that all loadings were significant, with Interested and Distressed fixed to 1.0 in order to scale the latent PA
Figure 4. Global Analyses: Perceived Health Factor Measurement Model Results

Figure 5. Global Analyses: PA and NA Factor Measurement Model Results; see Table 8 for Model Fit Indices.
and NA factors, respectively. The final models include residual covariances estimated based on initial modification indices.\(^3\) The model fit indices for each of these measurement models demonstrate good fit, according to the criteria noted on page 50.

4.3.2 Structural Models

The parameter estimates, standard errors, and p-values of the structural model parameters are shown in Table 9 for each structural model; Figures 6-12 illustrate these results. Note that the mixture modeling procedure used in the estimation of the latent interaction parameters does not permit standard model fit indices to be calculated; for this reason, only the log-likelihood values are displayed for these models in Table 9.

*Initial model.* The initial structural model testing the effect of the latent Objective Health factor on the latent Perceived Health factor (Figure 6) revealed a significant effect in the hypothesized direction, such that having worse objective health predicted worse subjective health ratings ($\beta = 0.336, p = .003$). The model fit indices demonstrate excellent fit, as the $X^2$ is non-significant ($p = .09$), the CFI is nearly 1.0 (.96), and the RMSEA is equal to .05.

*PA moderation model.* The model testing the individual biasing effect of global positive affect came next (Figure 7). Both direct effects were significant, such that worse objective health was significantly associated with worse perceived health, as before ($\beta = 0.310, p = .008$); and higher positive affect was linked with better subjective health evaluations ($\beta = -0.380, p < .0001$). The PA*Objective Health interaction parameter,

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\(^3\) For PA, residual covariances were estimated for active/enthusiastic, cheerful/relaxed, interested/inspired, and strong/active. For NA, residual covariances were estimated for scared/afraid, irritable/hostile, and jittery/nervous. These parameters were estimated in all structural models as well, and each was significant throughout ($p < .05$).
### TABLE 9

**STRUCTURAL MODELS FOR GLOBAL HEALTH BIAS ANALYSES**

<table>
<thead>
<tr>
<th>Parameter Estimate</th>
<th>Unstandardized</th>
<th>SE</th>
<th>p-value</th>
</tr>
</thead>
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<tr>
<td><strong>Structural Model Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Initial Structural Model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Objective Health → Perceived Health</td>
<td>0.336</td>
<td>0.114</td>
<td><strong>0.003</strong></td>
</tr>
<tr>
<td>Disturbance Estimate—Perceived Health</td>
<td>0.464</td>
<td>0.118</td>
<td><strong>0.000</strong></td>
</tr>
<tr>
<td><strong>PA Moderation Model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Objective Health → Perceived Health</td>
<td>0.310</td>
<td>0.118</td>
<td><strong>0.008</strong></td>
</tr>
<tr>
<td>PA → Perceived Health</td>
<td>-0.380</td>
<td>0.101</td>
<td><strong>0.000</strong></td>
</tr>
<tr>
<td>PA*Objective Health → Perceived Health</td>
<td>0.043</td>
<td>0.151</td>
<td>0.773</td>
</tr>
<tr>
<td>Affect/Health Covariance</td>
<td>-0.056</td>
<td>0.059</td>
<td>0.342</td>
</tr>
<tr>
<td>Disturbance Estimate—Perceived Health</td>
<td>0.392</td>
<td>0.113</td>
<td><strong>0.000</strong></td>
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<tr>
<td><strong>NA Moderation Model</strong></td>
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<td></td>
</tr>
<tr>
<td>Objective Health → Perceived Health</td>
<td>0.308</td>
<td>0.102</td>
<td><strong>0.003</strong></td>
</tr>
<tr>
<td>NA → Perceived Health</td>
<td>0.257</td>
<td>0.102</td>
<td><strong>0.012</strong></td>
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<tr>
<td>NA*Objective Health → Perceived Health</td>
<td>-0.187</td>
<td>0.089</td>
<td>0.036</td>
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<tr>
<td>Affect/Health Covariance</td>
<td>0.182</td>
<td>0.109</td>
<td>0.094</td>
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<tr>
<td>Disturbance Estimate—Perceived Health</td>
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<td>0.113</td>
<td><strong>0.000</strong></td>
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<tr>
<td><strong>Combined Moderation Model</strong></td>
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<td></td>
</tr>
<tr>
<td>Objective Health → Perceived Health</td>
<td>0.290</td>
<td>0.098</td>
<td><strong>0.003</strong></td>
</tr>
<tr>
<td>PA → Perceived Health</td>
<td>-0.339</td>
<td>0.099</td>
<td><strong>0.001</strong></td>
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<tr>
<td>NA → Perceived Health</td>
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<td>0.094</td>
<td>0.052</td>
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<tr>
<td>PA*Objective Health → Perceived Health</td>
<td>-0.001</td>
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<td>NA*Objective Health → Perceived Health</td>
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<td>PA/Health Covariance</td>
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<td>0.058</td>
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<tr>
<td>NA/Health Covariance</td>
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<td>PA/NA Covariance</td>
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<td>Disturbance Estimate—Perceived Health</td>
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<td>0.106</td>
<td><strong>0.001</strong></td>
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<td><strong>Day Bias Covariate Model—PA</strong></td>
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<tr>
<td>Objective Health → Perceived Health</td>
<td>0.308</td>
<td>0.114</td>
<td><strong>0.007</strong></td>
</tr>
<tr>
<td>PA → Perceived Health</td>
<td>-0.386</td>
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<td><strong>0.000</strong></td>
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<tr>
<td>Day PAbias → Perceived Health</td>
<td>-0.119</td>
<td>0.075</td>
<td>0.114</td>
</tr>
<tr>
<td>PA*Objective Health → Perceived Health</td>
<td>0.035</td>
<td>0.143</td>
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<tr>
<td>PA/Health Covariance</td>
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<td>Disturbance Estimate—Perceived Health</td>
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**TABLE 9 (contd.)**

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<th>p-value</th>
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<td>Objective Health → Perceived Health</td>
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<tr>
<td>NA → Perceived Health</td>
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<td>0.090</td>
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<tr>
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<td><strong>Final Combined Global/Day Model</strong></td>
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<tr>
<td>Objective Health → Perceived Health</td>
<td>0.279</td>
<td>0.092</td>
<td>0.003</td>
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<tr>
<td>PA → Perceived Health</td>
<td>-0.337</td>
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<td>0.000</td>
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<td>NA → Perceived Health</td>
<td>0.223</td>
<td>0.083</td>
<td>0.007</td>
</tr>
<tr>
<td>Day PAbias → Perceived Health</td>
<td>-0.133</td>
<td>0.074</td>
<td>0.071</td>
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<tr>
<td>Day NAbias → Perceived Health</td>
<td>-0.049</td>
<td>0.067</td>
<td>0.461</td>
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<tr>
<td>PA*Objective Health → Perceived Health</td>
<td>-0.004</td>
<td>0.132</td>
<td>0.974</td>
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<tr>
<td>NA*Objective Health → Perceived Health</td>
<td>-0.166</td>
<td>0.080</td>
<td>0.038</td>
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<td>PA/Health Covariance</td>
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<td>0.059</td>
<td>0.318</td>
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<tr>
<td>NA/Health Covariance</td>
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<td>0.127</td>
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<td>PA/NA Covariance</td>
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<td>0.061</td>
<td>0.006</td>
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<td>Disturbance Estimate—Perceived Health</td>
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<td>0.001</td>
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<td>Initial Structural Model</td>
<td>$X^2(19) = 27.53, p = .09; CFI = .96; RMSEA = .05$</td>
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<td>NA Moderation Model</td>
<td># Par: 71; -LL = 3909.97; AIC = 7691.95</td>
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<tr>
<td>Combined Moderation Model</td>
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<td>Day Bias Covariate Model (PA)</td>
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<tr>
<td>Day Bias Covariate Model (NA)</td>
<td># Par: 65; -LL = 3396.27; AIC = 6922.55</td>
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<tr>
<td>Final Combined Model</td>
<td># Par: 113; -LL = 5679.27; AIC = 11584.53</td>
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</tbody>
</table>

NOTE: Significant effects are **bold** (p ≤ .001); **bold italics** indicate p ≤ .01; **italics** indicate p ≤ .05; standard deviations are shown in parentheses. # Par = the number of parameters estimated in the model; -LL = log likelihood. AIC = Akaike Information Criterion; AIC permits the comparison of non-nested models, with lower values indicating better model fit.
Figure 6. Global Analyses: Initial Structural Model Results

Figure 7. Global Analyses: PA Moderation Model Results
however, was not significant, meaning that the link between objective health and subjective health perceptions was not biased by PA in this model.

**NA moderation model.** A similar story emerged in the individual NA bias model (Figure 8): the direct effects of both Objective Health ($\beta = 0.308, p = .003$) and Negative Affect ($\beta = 0.257, p = .012$) were significant, as was interaction parameter ($\beta = -0.187, p = .036$). Thus, we find evidence for the presence of NA health bias in this model.

![Figure 8. Global Analyses: NA Moderation Model Results](image)

**Combined moderation model.** When both PA and NA were included as latent moderators of the link between the Objective and Perceived Health factors (Figure 9), the only significant effects were for Objective on Perceived Health ($\beta = 0.290, p = .003$), PA on Perceived Health ($\beta = -0.339, p = .001$), and the covariance between the latent NA and PA factors ($\Psi = -.147, p = .023$). The fact that neither the direct effect ($p = .052$) nor the interaction parameter for NA ($p = .065$) maintain significance when the PA terms
are added to the model suggests that PA serves to counteract the impact of NA on global health perceptions, as was hypothesized. In this combined model, neither interaction effect is significant, indicating that neither affect factor biased global health perceptions.

*Daily PA bias covariate model.* The model sequence proceeded with the addition of the day-level bias covariates. The model testing the effects of global PA bias versus daily PA bias on global health evaluations (Figure 10) demonstrated the same pattern of results as was obtained in the model without the daily PA bias covariate. The direct effects for Objective Health ($\beta = 0.308, p = .007$) and PA ($\beta = -0.386, p < .0001$) were significant on Perceived Health, but neither the latent interaction parameter nor the day-level bias covariate had significant effects. Thus, the presence of day-level PA-biased health evaluations does not seem to impact more global subjective health ratings.

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4 The details concerning the estimation of these day-level affective health bias parameters are described in the results of the Daily Health Bias models (Section 4.4).
Figure 10. Global Analyses: Daily PA Bias Covariance Model Results

Daily NA bias covariate model. As was the case for the PA version of this model, the day-level NA bias covariate did not alter the pattern of results for the individual NA bias model (see Figure 11): the direct effects of both Objective Health ($\beta = 0.308$, $p = .003$) and NA ($\beta = 0.313$, $p < .0001$) were significant on Perceived health, as was the interaction effect ($\beta = -0.200$, $p = .021$). The effect of the daily NA bias covariate was not significant on the global Perceived Health factor. Once again, we have evidence for the presence of NA-biased health perceptions on the global level; an effect which is apparently unaffected by day-level bias patterns.

Daily combined bias covariate model. The final model in the global health bias sequence included tested all previous parameters at once, including the direct and interaction effects of both PA and NA bias, as well as both covariates representing day-
level NA and PA health bias (Figure 12). In this final combined model, all three direct effects were significant: worse Objective Health predicted worse Perceived Health ($\beta = 0.279$, $p = .003$), higher PA predicted better Perceived Health ($\beta = -0.337$, $p < .0001$), and higher NA predicted worse Perceived Health ($\beta = 0.223$, $p = .007$). The NA interaction effect on global perceived health was again significant ($\beta = -0.166$, $p = .038$), and the day-level PA bias covariate reached trend significance ($p = .071$). The covariance between the latent PA and NA factors was significant ($\Psi = -.168$, $p = .004$).

Global analyses: Overall story. Considering all models, the results supported the hypothesis that trait NA would exacerbate the association between objective and subjective measures of health on the global level, but revealed no evidence for the predicted PA bias. Both PA and NA factors did have direct effects on subjective health, however, even when both were included in the final combined model (Figure 12). Thus,
only trait NA serves to moderate the link between objective and perceived health, even when PA factors and day-level bias effects are considered (Figure 12); additionally, having higher levels of overall PA and/or lower levels of overall NA promotes more positive global health evaluations, as compared to the health perceptions of those with lower levels of global PA and/or higher levels of global NA. Note that the substantial reduction in the Objective–Subjective Health association—from 0.336 in the initial structural model (Figure 6) to anywhere from 0.279 (final combined model; Figure 12) to 0.310 (PA moderation model; Figure 7)—may also indicate a more mediational process at work, in which affect serves as an intermediary mechanism explaining this association; based on the estimates, PA appears to be the most potent affective domain in this respect.

Additionally, the presence of day-level affective bias does not appear to influence health evaluations made more globally, although a comparison of the log-likelihood and
AIC values do indicate that the addition of the day-level bias covariates did contribute to significantly better model fit in all cases (PA moderation models, NA moderation models, and Combined models, with and without daily covariates). Further, the fact that the effect of day-level PA health bias on Perceived Health neared significance in the final combined model ($p = .07$; Figure 12) suggests that day-level PA bias patterns may play a role in global health evaluations; future work should consider this further.

4.4 Analysis 2: Daily Health Bias

The next analytic phase tested for the effects of affect-associated health bias on the daily level. Results for the fixed effects of all models are shown in Table 10; random effects are shown in Table 11. The parameter estimates for the primary model paths are highlighted in Figures 13-19. Note that all day-level, random independent variables (health events, NA, PA) are centered around the person mean, such that a score of zero indicates that that person experienced levels of a given variable at their own average on a given day; mean terms for each of these variables were also included at Level 2. Day-level health satisfaction was the dependent variable in all models.

Intercept-only model. The first model omitted all independent variables, and only tested the effect of the intercept on the dependent variable (Model A). Both the fixed and random components of the intercept effect were significant; the intraclass correlation (ICC) calculation\(^5\) reveals that 68% of the overall variance is attributable to between-

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\(^5\) The ICC formula divides the within-person variance of the intercept ($\sigma_I^2$) by the sum of the intercept variance and error variance ($\sigma_I^2 + \sigma_e^2$) to arrive at the proportion of variance in the dependent variable attributable to between-person sources. The proportion of variance attributable to within-person sources can be found by subtracting this value from 1.0.
### Table 10

**Fixed Effects for Daily Health Bias Analyses**

<table>
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<tr>
<th>Parameter</th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
<th>Model D</th>
<th>Model E</th>
<th>Model F</th>
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<td>Intercept</td>
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<td>cEVENT</td>
<td>mPA</td>
<td>mNA</td>
<td>cPA</td>
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<tr>
<td></td>
<td>3.82 (0.057)</td>
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<td>-0.11 (0.015)</td>
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<td><strong>1664</strong></td>
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NOTE: Significant effects are **bold** (p < .01); **bold italics** indicate p < .05; standard deviations are shown in parentheses. LR Test = likelihood ratio test; bold type indicates a significantly better-fitting model. AIC permits the comparison of non-nested models, with lower values indicating better model fit.
### TABLE 11

RANDOM EFFECTS FOR DAILY HEALTH BIAS ANALYSES

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<th>Parameter</th>
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<th>Model PA**</th>
<th>Model NA</th>
<th>Model NA*</th>
<th>Model NA**</th>
<th>Model PA/NA</th>
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<td>17.1%</td>
<td>2.3%</td>
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<td></td>
<td>10.9%</td>
<td>1.6%</td>
<td>0.5%</td>
<td>20.4%*</td>
<td>2.4%**</td>
<td>0%</td>
</tr>
</tbody>
</table>

NOTE: Significant effects are **bold** (p < .01); **bold italics** indicate p < .05; standard deviations are shown in parentheses. Pseudo R^2 = the percentage of within-person variability explained by each additional variable.
person factors, whereas 32% is attributable to within-person factors. This indicates that it is appropriate to investigate the role of random (within-person) effects in future models.

*Day model.* The model testing for a significant slope parameter (i.e., a significant trend in daily health satisfaction across days) revealed a non-significant effect for Day (\( \gamma_{\text{DAY}} = -0.0002, p = .79 \)); for this reason, the Day parameter was not included in any subsequent day-level models.

*Initial direct-effects models.* The initial predictor model—Model EVENT in Tables 10 and 11—tested only the direct effect of a given day’s health events on that day’s health satisfaction (Figure 13). This association was significant (\( \gamma_{\text{HEV}} = -0.114, p < .0001 \)), such that experiencing more negative events on a given day was associated with lower overall health satisfaction that day, as would be expected. The random effect of the daily health events variable was significant as well (\( u_{\text{HEV}} = 0.024, p < .0001 \)), with the Pseudo R\(^2\) calculation demonstrating that the addition of this variable to the model explains an additional 9.4% of within-person variance in daily health satisfaction.

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![Image](image.png)

**Figure 13. Daily Analyses: Initial Health Model Results**
Although not shown in the tables, models also tested for the individual direct effects of daily PA and NA on health satisfaction, as described in Chapter 3 (Equations 11a-14d). Results from these models revealed that experiencing higher than typical levels of PA on a given day was associated with higher health satisfaction that day ($\gamma_{PA} = 0.031$, $p < .0001$), whereas higher levels of NA than usual for a given individual are linked with poorer daily health satisfaction ($\gamma_{NA} = -0.057$, $p < .0001$).

PA moderation model. The next models in the sequence tested for the individual direct effects and individual biasing effects of each affect on the link between daily health events and satisfaction. For PA, we find that there is a significant direct effect ($\gamma_{PA} = 0.028$, $p < .0001$), such that experiencing higher levels of PA is associated with higher health satisfaction (Model PA); this direct effect remains significant ($\gamma_{PA} = 0.026$, $p < .0001$) when the PA*Health Events interaction term is added to the model. The model testing for the PA health bias effect (Model PA*; Figure 14) revealed a significant interaction effect in the positive direction ($\gamma_{HEV*PA} = 0.006$, $p = .008$), such that experiencing levels of PA on a given day that are higher than one’s own average serves to buffer the negative impact of a day’s health events on that day’s health satisfaction. Thus, there is evidence for the presence of PA-biased health perceptions on the daily level, as was hypothesized. The Pseudo $R^2$ calculation revealed that the addition of the direct effect PA term explains an additional 17.1% of within-person variance in daily health satisfaction; the addition of the PA interaction/bias term accounts for an additional 2.3%.

NA moderation model. The same two models tested these effects for NA; the direct-effects NA model (Model NA) indicates a significant effect in the negative direction ($\gamma_{NA} = -0.047$, $p < .0001$), such that experiencing more NA on a given day is
associated with reduced health satisfaction that day; this effect maintains its significance ($\gamma_{\text{NA}} = -0.041, p < .0001$) when the NA*Health Event term is added. This interaction/bias model (Model NA*; Figure 15) reveals that there is a significant moderating effect ($\gamma_{\text{HEV*NA}} = -0.018, p = .006$), such that experiencing heightened levels of NA serves to exacerbate the within-day negative link between health events and health satisfaction. In terms of the random effects, the Pseudo $R^2$ calculation indicates that the addition of the direct-effect NA term explains an additional 10.9% of within-person variance as compared to Model EVENT; the NA interaction term accounted for an additional 1.6% of variance.
Combined moderation model. Next came the models testing these PA/NA effects simultaneously; Tables 10 and 11 show the results for Model PA/NA, which included terms testing the direct effects of both daily NA and PA on daily health satisfaction. We find that both direct effects maintain their significance ($\gamma_{PA} = 0.025, p < .0001; \gamma_{NA} = -0.027, p < .0001$) when the other affect term is included in the model (note that the absolute value of the PA estimate does not change substantially, whereas that for NA decreases substantially when compared to the single-affect-only models). Compared to Model EVENT, the addition of both direct effects explains an additional 20.4% of within-person variance; the NA term accounts for an additional 4% of the variance when compared to Model PA, whereas the PA term accounts for an additional 10.6% of the variance when compared to Model NA. Both direct effects remained significant ($\gamma_{PA} = 0.023, p < .0001; \gamma_{NA} = -0.024, p < .0001$) when both interaction terms were added to the model (Model PA/NA*; Figure 16), although only the NA*Health Event interaction was significant here ($\gamma_{HEVxNA} = -0.011, p = .03$); the PA bias effect was no longer significant ($\gamma_{HEVxPA} = 0.004, p = .08$) when the NA bias effect is included in the model. The addition of the interaction terms explained 2.4% of within-person variance over-and-above that explained by the direct-effects only model (Model PA/NA); the addition of the direct effect and interaction terms for NA explained 4.1% of the variance beyond the PA-only moderation model (Model PA*), whereas the addition of the PA terms explained 11.4% beyond the NA-only moderation model (Model NA*).

Global vs. Daily PA Bias model. Next came the models testing for the influence of global/trait-level affect on health satisfaction and health bias. First, Model PA** (Figure 17) included terms testing the direct effects and interaction effects of both day-
Figure 16. Daily Analyses: Combined PA/NA Moderation Model Results

Figure 17. Daily Analyses: Trait vs. Day PA Combined Model Results
level and global-level PA on daily health satisfaction. We see in Table 10 that the direct effect and interaction effect of daily PA remain unchanged when the global terms are added to the model ($\gamma_{PA} = 0.026, p < .0001$; $\gamma_{HEVxPA} = 0.006, p = .006$); the direct effect of trait PA on daily health satisfaction was significant in the positive direction ($\gamma_{PAtrait} = 0.020, p = .02$), such that having a greater overall tendency toward PA was associated with higher health satisfaction ratings on the daily level; the interaction parameter testing for the biasing effect of global PA was not significant ($\gamma_{HEVxPAtrait} = 0.002, p = .24$), indicating that when daily health evaluations are biased by PA, it is characterized by the current state-level experience, rather than a general mood tendency.

Global vs. Daily NA Bias model. The model testing the biasing effects of global NA on daily health satisfaction against those of day-level NA (Model NA**; Figure 18) revealed that, as was the case for the PA models, the parameter estimates for the direct effect of daily NA and the NA*Health Event interaction remained largely unchanged (and both maintained significance) when the global-level terms were added ($\gamma_{NA} = -0.041, p < .0001$; $\gamma_{HEVxNA} = -0.019, p = .004$). Neither the direct effect of global-level NA ($\gamma_{NAtrait} = -0.019, p = .16$), nor the global NA * Daily Health Event interaction effect ($\gamma_{HEVxNAtrait} = -0.001, p = .76$), had a significant impact on daily health evaluations.

Figure 18. Daily Analyses: Trait vs. Day NA Combined Model Results
Final Combined model. Finally, Model PA/NA** tested the effects of all terms (direct effects and interactions, daily and global affect terms) simultaneously (Figure 19). The results in Table 10 reveal that, when all levels and valences of affect are considered together, daily PA has a positive association with daily health satisfaction ($\gamma_{PA} = 0.023$, $p < .0001$); daily NA has a negative effect on daily health satisfaction ($\gamma_{NA} = -0.024$, $p < .0001$); daily NA serves to exacerbate (negatively bias) the within-day association between health events and health satisfaction ($\gamma_{HEVxNA} = -0.011$, $p = .02$); and global PA predicts more positive day-level health evaluations ($\gamma_{PA\text{trait}} = 0.022$, $p = .01$). The daily biasing parameter for PA reached trend significance here ($\gamma_{HEVxPA} = 0.004$, $p = .07$), and neither of the global affect bias terms were significant ($\gamma_{HEVxPA\text{trait}} = 0.001$, $p = .35$; $\gamma_{HEVxNA\text{trait}} = 0.001$, $p = .49$). Thus, the only statistically significant affective health bias present was for day-level NA; all other affects did not bias daily health perceptions.

Figure 19. Final Global vs. Daily PA/NA Combined Model Results
Daily Analyses: Overall Story. Overall, although the addition of each term improved overall model fit (as indicated by the likelihood ratio tests in Table 10), it appears that the primary factor contributing to day-level affective health bias is affect that occurs at the more situational, or state, level, rather than one’s general affective tendency; this was demonstrated in the models testing for the simultaneous biasing effects of day-vs. trait-level affect (Models PA** and NA**). When both positive and negative daily affect are considered, the level of negative affect on a given day appears to have the greatest biasing impact on health perceptions, as PA bias is no longer significant in the combined models.
CHAPTER 5:

DISCUSSION

As outlined in the introduction, this project draws on the existing literature in the areas of affect theory, health bias, and aging, investigating the role of both day-level affective experience and trait-level affective characteristics in serving to bias older adults’ momentary and global self-perceptions of health. The unique components of this study—the use of broader-spectrum affect measures, the exploration of health bias processes across levels of evaluation and analysis, and the more general conceptualization of health bias using a non-clinical sample—each align with gaps in the literature, leading the results to contribute to a more complete understanding of health bias processes in older adults.

Overall, the primary findings emerging from the analyses are 1) that trait NA does serve to bias global health evaluations, but trait PA does not; 2) that both daily PA and NA significantly bias day-level health perceptions, although only NA maintains its significance when both affective bias parameters are tested; and 3) that none of the cross-level effects were significant when both trait- and day-level bias parameters were tested simultaneously. Each of these findings—in addition to other relevant results that emerged from the analysis—is discussed below, within the context of the hypotheses and existing literature presented in the introduction.
5.1 Global Health Bias: Primary Findings

Considering the three primary investigative components of the project—global health bias, daily health bias, and health bias across levels—the global health bias element is perhaps most informed by the existing literature on affect-biased health perceptions, particularly for the models focused on NA bias. The primary hypotheses were that trait NA would exacerbate the relationship between global-level objective and perceived health, whereas trait PA would buffer that relationship; these expectations mirror the processes established in the literature and cited in the introduction (Benyamini et al., 2000; Bogaerts et al., 2008; Bogaerts et al., 2005; Karsdorp et al., 2007; Mora et al., 2007; Pettit et al., 2001; Powell et al., 2008; Pressman & Cohen, 2005; Rietveld & Van Beest, 2006; Strigo et al., 2008; Watson & Pennebaker, 1989). Additionally, based on the ideas of Broaden and Build Theory (Fredrickson, 1998), the buffering impact of PA was expected to counteract or “undo” the exacerbating effect of NA when both affective interactions were tested simultaneously.

The hypothesis regarding global NA bias was largely confirmed through the significant interaction parameters across models (Figures 8, 11, and 12), and supported by the nearly-significant bias parameter in the Combined moderation model (Figure 9; $p = .065$). No evidence for the presence of PA-biased health perceptions emerged in the global analysis, however. The direct effects hypotheses were largely confirmed, as Objective Health, PA, and NA each impacted Perceived Health in the hypothesized direction; that is, being less healthy and endorsing higher levels of trait NA predicted worse subjective health evaluations, whereas higher levels of trait PA were associated with better perceived health. Thus, the global-level results partially aligned with previous
experimental findings in the area, which have found trait-level affect (particularly NA) to bias health perceptions (e.g., Bogaerts et al., 2008; Bogaerts et al., 2005; Karsdorp et al., 2007; Mora et al., 2007; Strigo et al., 2008); the significant NA bias effects also support the ideas of Symptom Perception Theory (Gijsbers van Wijk & Kolk, 1997), which identifies trait-level NA characteristics as the primary mechanism underlying biased health perceptions.

The “undoing” hypothesis based on Broaden and Build theory (Fredrickson, 1998) was also partially confirmed, as the significant NA biasing effect present in the NA moderation model (Figure 8) became non-significant when PA was added (Figure 9); thus, we have evidence that trait PA serves to “undo” the biasing effect of trait NA, even though it does not bias perceived health evaluations itself. There is also evidence for this undoing effect when we examine the direct links between trait affect and global perceived health. Specifically, whereas NA significantly predicted perceived health in the NA Moderation Model (Figure 8), its effect was no longer significant in the Combined Moderation Model (Figure 9), when the impact of PA was included in the model; so, the significant direct effect of PA on global health perceptions appears to mediate—or “undo”—the negative influence of trait NA in this case. It is interesting, however, that these NA parameters maintain significance when PA is included in the combined model (Figure 12), where the only difference is the addition of the day-level bias covariates.

Although the moderating effect of PA in the form of health bias was of interest here, there is evidence for a mediational process occurring instead; that is, in all cases in which trait level affect was added to the model, the parameter estimate for the Objective–Subjective health association was substantially reduced. So it may be that, on the global
level, rather than this link depending on trait affect, it partially operates through trait affect, so that having poorer health leads to more negative affect and/or less positive affect, which in turn results in more negative subjective health evaluations; likewise, having better objective health leads to less negative affect and/or more positive affect resulting in more positive health-related perceptions. In other words, it may be that the operationalization of health bias here—defined as the interaction between affect and objective health on perceived health—is inappropriate on the global level, at least for PA; rather, the trait-level biasing effect may be more accurately captured by the direct association between global affect and subjective health evaluations when objective health indicators are controlled; the latter conceptualization does align with some previous work in the area (e.g., Main et al., 2003; Pressman & Cohen, 2005; Watson, 1988). Future studies should investigate the utility of each of these conceptualizations of health bias, in order to more fully understand these processes and how they may operate differently depending on the level of evaluation and analysis.

5.2 Daily Health Bias: Primary Findings

Once again, the expectation on the daily level was that daily PA would buffer the negative association between a given day’s health events and that day’s health satisfaction, whereas daily NA would exacerbate this within-day link, thereby demonstrating the presence of health bias. The findings supported this hypothesis, as the individual affect moderation models (Models PA* and NA*) each revealed significant interaction (bias) effects.

The hypothesis that day-level PA health bias would serve to “undo” or counteract the impact of day-level NA bias was partially supported: the parameter estimate for the
NA bias effect went from -0.018 (p < .01) in Model NA* to -0.011 (p < .05) in Model PA/NA*; however, the fact that the NA bias parameter retained its significance in the combined model—whereas the PA bias parameter did not—indicates that, although both positive and negative affects can bias daily health perceptions, experiencing levels of NA higher than one’s own average on a given day is the most potent predictor of between-person differences in daily health bias.

Note that this pattern of results is different from that which emerged from our previous work in the area—in our preliminary work, when both positive and negative daily bias parameters were tested simultaneously, the PA bias parameter retained significance whereas the moderating effects of high- and low-arousal NA did not (Whitehead & Bergeman, 2013). These conflicting results are likely related to the different samples used in the two studies: the present study used a sample exclusively comprised of older adults, whereas the previous study used a sample spanning in age 33 to 80. There is evidence that, although the experience of positive emotions is higher or more pleasurable in late life (i.e., the paradox of well-being; Windsor & Antsey, 2010), the salience of negative emotions becomes much stronger (Whitehead & Bergeman, 2012). Because of the potential for increased avoidance of negative emotions, as outlined in Socioemotional Selectivity Theory (Carstensen, 1995; Carstensen, Isaacowitz, & Charles, 1999), the greater potency of NA bias found in the present sample of older adults is likely capturing this heightened salience. Additionally, the previous study examined the biasing effects of low-arousal and high-arousal NA separately, whereas these two domains were collapsed into a single NA dimension in the present study; it may be that this combined NA factor has stronger biasing effects than the arousal-split
constructs, thereby altering the relationship between the PA and NA biasing effects. Thus, although these differences do recommend some caution in generalizing the day-level bias results of the present study beyond the specific age group and affect conceptualization used here, they also present interesting avenues for future research; studies systematically examining age effects in health bias processes, or considering the differential biasing functions of anxiety versus depressive components of negative affect, would shed light on the mechanisms behind these discrepancies.

Further, despite the non-significant effect for PA bias in the combined model, it is important to note that the PA effects in the current study (both direct and moderating) do explain a larger portion of within-person variability than do the NA effects, perhaps indicating that PA plays a greater role in daily health bias processes within individuals, whereas NA is more predictive of differences in biased daily health perceptions between individuals. This was the case in the previous paper as well (Whitehead & Bergeman, 2013), indicating that this pattern may be more consistent across age groups and contexts than some of the fixed effects. These findings align with the idea that PA processes are more situationally-based, whereas NA processes originate from more personality-level tendencies (e.g., Watson, 1988), and partially supports the cross-level hypothesis to that effect.

Overall, these findings largely align with those of existing studies examining day- or state-level affective health bias (e.g., Baker et al., 1992; Bogaerts et al., 2005; Main et al., 2003; Watson, 1988; Whitehead & Bergeman, 2013) and support the ideas of the Cognitive-Affective model (Janssens et al., 2009; Petersen et al., 2011), although they extend their purview. Specifically, these results highlight the presence of day-level health
bias processes within a general evaluative context, rather than within a specific symptom paradigm (e.g., Main et al., 2003); the daily diary format utilized here is also more representative of these processes as they occur on the everyday level, as opposed to experimental studies that tend to capture processes at only a single point in time, thereby limiting the generalizability of findings (e.g., Baker et al., 1992; Bogaerts et al., 2005). Future studies should continue to investigate the extent to which these more general health bias processes are similar to or different from those that manifest within specific diagnostic conditions, as well as more explicitly explore the extent to which high- vs. low-arousal affects—which were only represented here within the affect variables—differentially impact the presence and strength of day-level health bias effects, as was done initially by Whitehead and Bergeman (2013).

5.3 Cross-Level Analyses: Primary Findings

The cross-level models testing for the differential impact of state vs. trait affective experience on both global and daily health bias processes failed to demonstrate significant cross-level effects, contrary to hypotheses. That is, in the global models, the day-level PA and NA bias covariates did not significantly impact the latent Perceived Health factor, although the PA day bias covariate did reach trend significance in the final combined model \( (p = .07; \text{ Figure 12}) \), with the effect being in the hypothesized direction (i.e., a greater presence of PA bias on the daily level being linked with more positive perceived health ratings globally). This borderline significance may be a factor of the relatively small sample size, as a larger sample would have greater power to detect any real effects that were not identified here. Likewise, in the daily models, the trait affect variables failed to moderate the link between daily health events and health satisfaction,
although Trait PA did have a direct effect. Overall, then, it appears that health bias processes are largely constrained within level (i.e., daily affect → daily health bias, global affect → global perceived health), as opposed to trait affect determining day-level processes or day-level bias influencing trait-level perceptions. So, the hypotheses that trait-level NA would influence day-level NA bias, and that day-level PA bias would mediate the effect of global PA health bias were not supported in the present sample.

Taken together, this pattern of results sheds light on the manner in which day-level affective experiences and trait-level affective tendencies influence health perceptions; specifically, being in a negative mood when reporting or reflecting on one’s current health can lead the individual to under-evaluate their healthiness or over-report symptoms; similarly, having a trait-level tendency toward negative affect can negatively bias an individual’s more general perceptions and evaluations about his or her own health. Being in a positive mood or having a tendency toward PA, however, does not appear to bias subjective health evaluations, whether they are made on the global or daily level; there is, however, evidence that PA counteracts NA bias to an extent.

So, it may be that priming a positive mood and/or orienting an individual to his or her PA traits may alleviate the bias and lead to more accurate health reports. This information could be quite helpful in applied settings, such as the collection of self-reported health data in academic research situations, or the physician’s initial assessment of health status, based on patient self-report. For example, researchers could have participants watch an uplifting clip, listen to upbeat music, or think about a positive anecdote prior to completing subjective health measures; in a large survey booklet, simply preceding the subjective health scales with a positive measure could be sufficient
to alleviate any NA bias that may occur otherwise. It is also important for researchers to include assessments of trait and state-level affect in their research designs in order to control for these biases if necessary.

Physicians can take a similar approach, although in a more informal manner—prior to asking, “how are you feeling today?” physicians could ask questions intended to orient the patient to a more positive response framework (e.g., “so, did you do anything fun last weekend?”); this could not only counteract some of the negative bias that is caused by state- and trait NA, but also serves to build rapport and put the patient more at ease in what is often a stressful situation. Medical professionals could also attempt to assess affect in order to account for it in their interpretations of the patient’s responses, perhaps by asking about their mood of late. This line of questioning would also provide a pre-screen for the presence of psychological disorders such as depression and anxiety, which lead to more extreme perceptual biases and health issues than more moderate levels of affect. Such screening for potential mood disorders and psychopathology is an increasingly important component of a regular physical exam, as it is becoming apparent that the general practitioner is often the only health professional to come in contact with patients, and represents a valuable first line of defense in the recognition and early intervention of mental health issues.

5.4 Limitations and Future Directions

Although the current project was designed to bridge a number of gaps present in the health bias literature, it is not without its limitations. First, because the data is drawn from a larger project investigating a myriad of health and well-being processes in midlife and older adults, the measures and methods were not developed and/or selected
specifically with the present project in mind; this restricts the operationalization of the constructs of interest to the measures included in the larger project, which in some cases may not be optimal. For example, in the case of the measure of perceived health on the daily level, the single item included in the daily diary—“Overall, how satisfied are you with your health today?”—may not be as informative to the question at hand as would an item or items more similar to those used on the global level (e.g., “Overall, how would you rate your health today?”). The timing of assessments, which were carefully designed for the larger project, is also less ideal than it would be if the data collection procedures had been designed specifically for the present purpose. For example, the affect and perceived health measures used in the global analyses were taken at a different time and location than were the in-person objective health assessments, although they tended to be within a few months of each other. Despite issues like these, the rich data provided by the NDHWB project makes the investigation of the complex questions of interest possible, as the collection of such a dataset for the current project alone was not feasible; results of the present project therefore lay the groundwork for future studies that will be explicitly designed to test the processes investigated here.

A second limitation is also a function of the available data: specifically, the conceptualization of health bias is not as neatly comparable between levels of analysis as it would be if global and daily measures of objective and subjective health were more similar; the most evident discrepancy is in the operationalization of objective health across levels, as the physiological indices on the global level is replaced with a self-reported event checklist on the daily level. This limits the conclusions that can be drawn from the results of the global vs. daily analyses, but also provides an opportunity for
future projects to build on the findings. A particularly interesting next step would be to collect a number of physiological indicators that can be somewhat variable from day to day (e.g., cortisol, blood pressure, heart rate, morning glucose levels) to index daily objective health, in order to more directly mirror the physiological aspect of objective health on the global level. Results from a study like this would permit stronger conclusions to be drawn regarding the relationship between health bias processes on the global and daily level.

Finally, the sample used here consists only of older adults, which means that the present results are not generalizable to populations at other points in the lifespan. As noted previously, there is evidence that both affect and health perceptions—or at least their cognitive correlates—change with age (e.g., Ashby et al., 1999; Carstensen et al., 1999; Kriegsman et al., 1996; Lagaay et al., 1992; Park-Lee et al, 2009; Whitehead & Bergeman, 2012; Windsor & Anstey, 2010; Yong et al., 2001); because objective health naturally declines with age as well, it may be that the associations found here would be different in samples reflecting other points in the adult lifespan. Future research should certainly undertake the investigation of how the health bias processes investigated here may change or remain the same with age.

In addition to the future directions mentioned in the context of these limitations, there are several avenues that researchers could pursue based on the results of the present project. For example, it would be interesting to expand the investigation to explore how multiple aspects of the person and the environment (e.g., personality, season, room characteristics, and so on) impact the presence and manifestation of affect-biased health perceptions on the state and trait level. Once establishing the presence and role of affect
on biased health perceptions in a more general health context, it is also important to look at whether the extent of bias depends on a specific diagnosis or symptom schema, or if bias manifests in largely the same way across contexts. Another important direction is to explore how these health biases—particularly those present on the trait level—impact long-term health and well-being outcomes; it may be that longitudinal studies will find that positively- or negatively-biased health perceptions may be adaptive for some people or in certain contexts. It is also important for future projects to pursue the explicit role of affective arousal in the presence and manifestation of health bias across levels, which would be possible with the assessment of a greater number of low- and moderate-arousal affect items than was used here.

A particularly important next step in this vein would be to investigate the extent to which biased health perceptions influence health-related behaviors, which are likely to serve as the primary mechanism explaining the link between biased perceptions and health outcomes. There is a substantial literature within the medical field on the presence of inaccuracies and biases in elders’ self-reports of health (Bergmann et al., 1998; Haapanen et al., 1997; Jordan et al., 1999; Kehoe et al., 1994; Nilsson et al., 2002). There have also been studies conducted within psychological and healthcare contexts examining the associations between health behaviors and health outcomes (e.g., Proper, Singh, van Mechelen, & Chinapaw, 2011). There is a paucity of research, however, on the link between the extent of bias present in one’s perceptions of their own health and their subsequent health behaviors, such as lifestyle choices and healthcare utilization. Because perceptions and beliefs about oneself and one’s health are likely to impact decisions related to diet, activity level, use of over-the-counter or alternative medicines, utilization
of preventive and emergency care, and contacts with medical professionals—which in turn influence long-term morbidity and mortality—this is an important mechanism to explore.

More specifically, if one’s self-health reports and perceptions are positively biased, then he or she may not be as aware of potential issues and may take less care in considering long-term health ramifications of everyday health decisions; this may lead to poor prognosis down the line, as poor health monitoring results in undetected or ignored illness. On the positive side, however, they may continue an active lifestyle longer than they may have if they “knew” that their health was worse than they thought; this, along with the mental health benefits of having a positive frame of mind, may actually promote health, or at least buffer the deleterious impact of positive bias on health behaviors. On the other hand, if one’s health perceptions are biased by negative affect, he or she may be hypersensitive to any given malady and over-utilize medications and physician visits, placing undue burden on the already overwhelmed healthcare system. It is also likely, however, that the additional vigilance of these individuals leads to early detection of diseases that do exist, perhaps serving to promote their health in the long run, assuming the negative mindset is not so pervasive that it has a deleterious impact on other facets of functioning. A study investigating these behavioral links would shed greater light on the extent to which the biased health perceptions explored here have long-term ramifications on health, or if their role is largely restricted to the realm of information inaccuracies suggested in the introduction.

5.5 Conclusion
Overall, the present study contributes to the literature in a number of ways, by empirically informing: a) the biasing effects of both positive and negative affect in the context of perceived health, as opposed to negative affect only; b) the use of moderate- and low-arousal affect items—in addition to high-arousal affects—in scales of positive and negative affect, permitting the findings to be generalizable to a broader affective space than studies using only activated (high-arousal) affect scales; c) the presence and nature of affect-biased health perceptions on both trait (global) and state (daily) levels, rather than only one or the other; d) the combined effects of health bias processes across trait and state levels, which permit professionals who rely on self-reported health information to better understand and counteract the most salient predictors of bias; and e) the conceptualization of health bias in a general, non-diagnosis- or symptom-specific manner, which will shed light on health bias processes as they operate broadly in the everyday lives of older adults. The results lay the groundwork for a myriad of future studies, which will continue to shed light on the antecedents and consequences of affect-related health bias.


