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The Role of Affect on Physical Health Over Time: A Cross-Lagged Panel Analysis Over 20 Years

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Background: While previous studies have investigated the interplay between affect and health (1) over an extended period of time, (2) in a representative population, and (3) while modelling positive and negative affect simultaneously, no single study has done all three at once. **Methods:** The present study accomplishes this by sampling adults from the Midlife Development in the US study who completed affect (Mroczek & Kolarz, 1998) and health measures (chronic conditions, Charlson, Szatrowski, Peterson, & Gold, 1994; functional limitations, McHorney, Ware, Lu, & Sherbourne, 1994; self-reported health) measured three times over 20 years. We ran three (one per health metric) random-intercept cross-lagged panel models, where positive and negative affect were modelled simultaneously. **Results:** Results indicated that positive and negative affect significantly predicted future heath (functional limitations/self-reported health) and that this relationship was reciprocal (i.e. health measures predicted future affect). However, there were no significant cross-lagged relations between affect and chronic conditions. **Conclusion:** Our results suggest that both positive and negative affect play an equal role in predicting future health for functional limitations and self-reported health as well as highlight the bi-directionality of this relationship. Additionally, the degree to which affect predicts future health may be moderated by the type of health outcome.

Keywords: affect, cross-lagged, health, longitudinal, well-being

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INTRODUCTION

To what extent does affect contribute to physical health over time? A large body of literature supports the idea that affect can influence health over the course of days, weeks, and months (Pressman & Cohen, 2005; Salovey, Rothman, Detweiler, & Steward, 2000). There is increasing interest in extending these findings over longer periods of time as it has been theorised that affect may have even longer-term consequences for physical health over many years (e.g. Diener & Chan, 2011). Despite this interest, research on this topic remains equivocal (e.g. Diener, Pressman, & Lyubomirsky, 2015; Liu et al., 2016) and there is a need for additional research to explore extended temporal dynamics between affect and health.

The goal of the current study is to extend previous research on the temporal dynamics between affect and health by (a) using data collected over 20 years, (b) using a nationally representative sample, and (c) simultaneously modelling positive and negative affect to enable comparisons between the two. Exploring this relationship over longer periods, in a representative sample, and modelling positive and negative affect simultaneously will help clarify the role affect—and the valence of affect—plays in the etiology of physical health outcomes.

Affect and Physical Health

There are varying perspectives and definitions of affect with one major view being a valence-based evaluation of life experiences (DeSteno, Gross, & Kubzansky, 2013). Affect operates as a relatively stable lens through which individuals perceive their everyday experiences (Johnson & Tversky, 1983) and is often discussed in terms of positive valence (positive affect) and negative valence (negative affect; Watson, Clark, & Tellegen, 1988). With respect to health, negative affect is commonly thought to increase the risk of harmful health conditions, whereas positive affect is argued to decrease this risk and promote physical health (DeSteno et al., 2013). We discuss below how different valences of affect can influence physical health through adopting the main effects model.

The main effects model posits that affect can either directly influence health outcomes through emotionally sensitive health systems (e.g. cardiovascular, immune) or indirectly through mediating behaviours (e.g. exercise, sleep, eating habits; Cross & Pressman, 2017; Pressman & Cohen, 2005). Positive affect has been shown to have salutary effects on both health-related systems and healthy behaviours. High levels of positive affect are associated with better immunity (Cross & Pressman, 2017; Marsland, Pressman, & Cohen, 2007), cardiovascular health (Boehm & Kubzansky, 2012), and overall physical health/longevity (Lee, Hsieh, & Paffenbarger, 1995; Pressman & Cohen, 2005). Further, positive affect has been shown to influence decision-making processes regarding healthy behaviours (Steptoe, Dockray, & Wardle, 2009). Indeed those with high levels of positive affect tend to engage in less risky behaviour (Carrico, Johnson, Colfax, &

Moskowitz, 2010), adopt better coping strategies in the face of stress (Folkman & Moskowitz, 2000), and participate in more physical activity (Watson, 1988).

Further, there is evidence supporting these direct and indirect effects with regard to negative affect (e.g. Kiecolt-Glaser, McGuire, Robles, & Glaser, 2002). The deleterious direct effects of negative affect can be seen in the research on health-related systems, where those with higher levels of negative affect are at an increased risk of contracting infectious diseases (Cohen, Tyrrell, & Smith, 1993), experiencing cardiovascular episodes (Roest, Martens, de Jonge, & Denollet, 2010), and morbidity (Kiecolt-Glaser et al., 2002). Additionally, high levels of negative affect can influence an individual's decision-making processes and subsequent behaviours (Isen, 1987; Keltner & Lerner, 2010), which can have implications for physical health. Individuals with high negative affect are less likely to seek continued medical care (Mora, Robitaille, Leventhal, Swigar, & Leventhal, 2002), are prone to adopting ineffective coping strategies to deal with stress (Billings, Folkman, Acree, & Moskowitz, 2000), and engage in less physical activity (Andersen, Kiecolt-Glaser, & Glaser, 1994). The current evidence on the affect–health relationship supports a meaningful linkage. Yet, there are still questions regarding how this relationship may unfold over longer periods of time.

Temporal Considerations

Affect is argued to have both temporally proximal (Barrett & Bliss-Moreau, 2009) and distal (Cross & Pressman, 2017) effects on health. Yet, most of the research to date tends to focus on the former, linking affect with health over a number of days, weeks, or years (Pressman & Cohen, 2005; Salovey et al., 2000). Expanding the period to decades is an important consideration in recognition of their long-term effects (Diener, Pressman, Hunter, & Delgadillo-Chase, 2017). Studies considering this relationship over decades tend to focus on mortality rather than health (e.g. Danner, Snowdon, & Friesen, 2001; Koivumaa-Honkanen et al., 2000), leaving questions on how affect relates to health over longer periods unanswered. Further, efforts investigating the temporal effects over shorter terms often focus on non-representative samples (e.g. elderly, cancer patients) or do not model positive and negative affect simultaneously, which should be considered when interpreting the external validity of their results. Below, we briefly discuss why investigating the temporal dynamics in a representative sample and modelling both types of affect is crucially important.

Studies using specific populations can inform us about the linkage between affect and health. Specifically, these studies allow us to understand the importance of affect for populations such as the elderly (Ryff, Singer, & Dienberg Love, 2004), cancer patients (Cassileth, Lusk, Miller, Brown, & Miller, 1985), and heart-attack survivors (Blumenthal et al., 2005). Yet, in order to have a more general understanding of how affect influences health over time in the general population, it is important to examine this relationship in a sample that is representative of the broader population.

Further, to better understand the temporal dynamics of affect on health, positive and negative affect need to be modelled simultaneously. As discussed earlier, positive and negative affect are considered to influence physical health through similar mechanisms (e.g. health systems, behavioural choices) but there is debate within the literature concerning which valence of affect has stronger effects (e.g. Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). Previous research shows that, when modelled simultaneously, both positive and negative affect are associated with health (e.g. Pressman, Jenkins, Kraft-Feil, Rasmussen, & Scheier, 2017), yet there is a need to investigate this relationship over longer periods of time.

The Present Study

As noted earlier, previous research has examined the relationship between affect and health over long periods of time, within representative populations and modelled both types of affect simultaneously. Yet, to the best of our knowledge, no study has examined this phenomenon combining all three dimensions. To achieve this, the present study simultaneously models positive and negative affect using a national sample of Americans from the Midlife Development in the US (MIDUS) surveyed over a 20-year period. The MIDUS sample is not restricted to any particular health condition, enabling us to estimate population-level affect and health. We examined this relationship through random-intercept cross-lagged panel analysis (Hamaker, Kuiper, & Grasman, 2015), where we simultaneously model positive and negative affect in prediction of three physical health outcomes (number of chronic conditions, self-reported health, and functional limitations). The cross-lagged analysis also allows us to estimate the strength of the bidirectional effects between affect and health. Further, the inclusion of a random-intercept in the cross-lagged panel model controls for the stability of a construct over time, producing more accurate estimates of the cross-lagged relations (Hamaker et al., 2015). Altogether, we set out to examine the following research questions.

Research question 1a: Does positive affect predict future health outcomes when negative affect is modelled simultaneously?
Research question 1b: Does negative affect predict future health outcomes when positive affect is modelled simultaneously?
Research question 2: To what degree does health predict future affect?

METHOD

Participants

Data are from all three waves of the Survey of Midlife Development in the United States (MIDUS), a longitudinal study of the physical and mental health of middle-aged and older adults. The first wave of data collection (MIDUS 1; N = 7,108, Age_{mean} = 46.38, Age_{range} = 20–75, 51% female) included a national probability sample of non-institutionalised English speaking adults living in the contiguous United States recruited by random digit dialing (RDD; n = 3,487), a sample of monozygotic and dizygotic twin pairs from a national twin registry (n = 1,914), oversamples from five metropolitan areas (n = 757), and siblings of individuals from the RDD sample (n = 950). Respondents completed telephone interviews and self-administered questionnaires (SAQ). Follow-up studies were completed in 2004–06 (MIDUS 2) and 2013–14 (MIDUS 3). Overall retention trends suggested a retention rate of around 70 per cent from MIDUS 1 (n = 7,097) to MIDUS 2 (n = 4,962) and a 66 per cent retention rate from Wave 2 (n = 4,962) to Wave 3 (n = 3,293). However, mortality-adjusted retention was 75 per cent between MIDUS 1 and MIDUS 2 and 77 per cent between MIDUS 2 and MIDUS 3. We used *Mplus* for our analyses, which utilises Full Information Maximum Likelihood (FIML). Using Maximum Likelihood Estimation embedded in *Mplus* is useful in dealing with endogeneity problems (e.g. Park & Gupta, 2009). Collection of data for all three waves of MIDUS and analyses for the current study were approved by the Institutional Review Boards at the University of Wisconsin-Madison and Purdue University, respectively.

Measures

Positive and Negative Affect. The positive and negative affect measure (Mroczek & Kolarz, 1998) asked individuals to indicate how many times over the past 30 days they experienced six positive emotions (e.g. "Cheerful", "Calm and peaceful") and six negative emotions (e.g. "Restless or fidgety", "Hopeless"). The scale for both measures ranged from 1 (*none of the time*) to 5 (*all of the time*). Positive affect (α = .90–.91) and negative affect (α = .84–.86) demonstrated sufficient internal consistency across the three waves.

Health. Three measures were used to assess health: self-reported health, functional limitation, and chronic conditions. For self-reported health, participants were asked to rate their current health on a scale from 0 to 10, with 0 representing the worst health and 10 representing the best health.

For functional limitations, participants were asked the degree to which their health impeded their ability to do nine everyday activities (e.g. walking one block, climbing stairs, bathing, or dressing) on a 4-point scale (1 = *a lot*; 4 = *not at all*). These nine activities were sourced from the SF-36 (McHorney, Ware, Lu, & Sherbourne, 1994). Scores on this measure were reversed such that a high score represented greater functional limitations.

For chronic conditions, participants were asked to report the number of chronic health conditions they had at each data collection wave. The purpose of the measure was to gather a large breadth of chronic conditions. While many of the chronic conditions included in this measure appear in other validated measures such as the Charlson Comorbidity Index (e.g. diabetes, stroke; Charlson, Szatrowski, Peterson, & Gold, 1994), others were included to increase the breadth of the measure (e.g. constipation). In total, there were 30 conditions they could respond to including lung conditions, urinary bladder problems, high blood pressure, and diabetes. In line with previous research (e.g. Wikman, Wardle, & Steptoe, 2011), we scored chronic conditions using an unweighted count (0–30), which has been shown to predict most outcomes equally well as more complex measures (Huntley, Johnson, Purdy, Valderas, & Salisbury, 2012).

Control Variables. Several demographic variables were used as control variables in this study. Specifically we used age (M = 46.38), gender (51% female), education, marital status, and personality scores measured at the first wave as control variables. Education was measured using a 12-point scale, with lower values indicating less education (e.g. no school, some high school) and high values indicating more education (e.g. masters degree, doctoral degree). Marital status was dichotomised (0 = *never married*; 1 = *married at some point*).

Personality variables were measured using the Midlife Development Inventory (MIDI; Lachman & Weaver, 1997). The MIDI comprises six personality traits: extraversion (5 items), agreeableness (5 items), neuroticism (4 items), conscientiousness (4 items), openness to experience (7 items), and agency (5 items). Participants were asked to indicate on a 4-point scale (1 = a *lot*, 4 = *not at all*) the degree to which each item-adjective described them. Five of the six traits demonstrated sufficient internal consistency (α = .75–.82), with conscientiousness exhibiting the lowest internal consistency (α = .56).

Analysis

We took a two-step approach to the analyses (De Jonge et al., 2001). First, we conducted a longitudinal confirmatory factor analysis to examine the measurement invariance of positive and negative affect over time (Biesanz, 2012). This was accomplished through a series of nested model comparisons with an increasing number of constraints. The first model assessed the similarity in factor structures across time (*configural invariance*). If there was evidence of configural invariance, restrictions were placed on the factor loadings to be equivalent across time (*metric invariance*). If there was evidence of metric invariance, the intercepts were constrained to be equivalent across time (*scalar invariance*).

At each stage of analysis, four goodness-of-fit indices were used to evaluate model fit: (1) the Comparative Fit Index (CFI; Bentler, 1990), (2) the Tucker-Lewis Index (TLI; Tucker & Lewis, 1973), (3) the Root Mean Square Error of Approximation (RMSEA; Steiger, 1990), and (4) the Standardised Root Mean

Square Residual (SRMR; Bentler, 1995). Traditional χ^2 statistics were not used as they are sensitive to large sample sizes—making it especially easy to reject the null hypothesis (Brannick, 1995; Kelloway, 1995). We used generally accepted criteria for the CFI (>.90), TLI (>.90), RMSEA (<.08), and SRMR (<.10) to indicate good fit (Browne & Cudeck, 1992). Further, we also assessed relative fit between models when adding model constraints to test measurement invariance. Specifically, the change in CFI is the preferred fit index when conducting longitudinal confirmatory factor analyses (Little, 2013). If the change in CFI is less than .01 after adding constraints, the two models are said to be equivalent (Cheung & Rensvold, 2002).

The second step of the analysis analysed the temporal dynamics between affect and health through the use of a random-intercept cross-lagged panel model. This type of model improves on the traditional cross-lagged panel model through the inclusion of a random-intercept. The random-intercept serves as a longitudinal component which can be thought of as multilevel data; specifying the random-intercept allows for the separation of within-person process from between-person differences, facilitating the study of causal influences in longitudinal panel data (Hamaker et al., 2015). The random-intercept cross-lagged panel model used in the current investigation can be found in Figure 1.

Next, we modelled the simultaneous effects of positive and negative affect on health in three different analyses—one for each measure of health. We also examined the degree to which these effects were consistent across time by testing a series of nested models with increasing constraints (Selig & Little, 2012). First, we tested freely estimated models (Model 0), followed by a model constraining the means to be equivalent across time (Model 1), then a model constraining the lagged paths (i.e. Model 2, the path coefficient between measurement of the same construct at different time points), then the cross-lagged paths (i.e. Model 3, the path coefficient between the measurement of different constructs at different time points), and finally the cross-sectional paths (i.e. Model 4, the covariance between different constructs at the same time point). We inspected the goodness-of-fit statistics and selected the most parsimonious model to estimate the effects of affect on health. In all cross-lagged models, we controlled for wave 1 reports of age, gender, education, marital status, and personality. These analyses were conducted in *Mplus* 7.3 (Muthén & Muthén, 2015).

RESULTS

Means, standard deviations, and zero-order correlations are all displayed in Table 1. Measurement invariance results for positive and negative affect are presented in Table 2. Results indicated that the configural (positive affect, CFI = .933, TLI = .910, RMSEA = .085, SRMR = .036; negative affect, CFI = .903, TLI = .870, RMSEA = .082, SRMR = .062), metric (positive

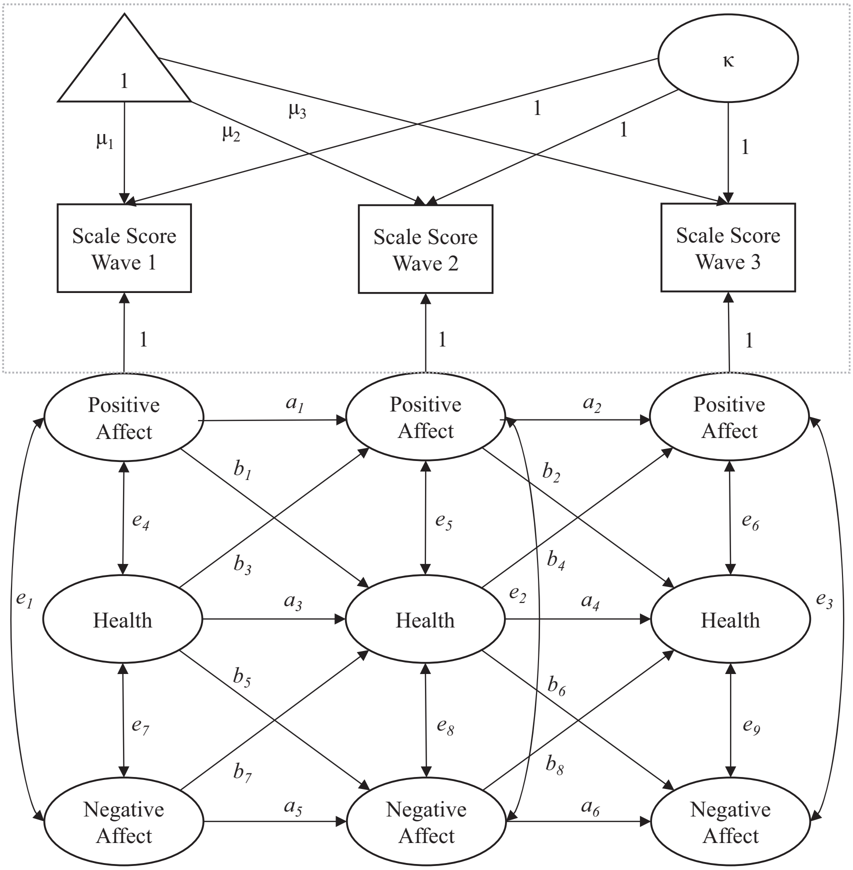

FIGURE 1. Graphic of the random-intercept cross-lagged panel model examined in the current study. Model 0: all paths are freely estimated; Model 1: means are constrained to be equal across time for each construct (i.e. $\mu_1 = \mu_2 = \mu_3$). Model 2: autoregressive lags are further constrained to be equal within each construct (i.e. $a_1 = a_2$, $a_3 = a_4$, $a_5 = a_6$). Model 3: cross-lags between the same constructs across time are further constrained to be equal (i.e. $b_1 = b_2$, $b_3 = b_4$, $b_5 = b_6$, $b_7 = b_8$); Model 4: in addition, covariance between constructs is constrained to be equal across time (i.e. $e_1 = e_2 = e_3$, $e_4 = e_5 = e_6$, $e_7 = e_8 = e_9$).

affect, CFI = .932, TLI = .916, RMSEA = .083, SRMR = .044; negative affect, CFI = .903, TLI = .880, RMSEA = .078, SRMR = .063), and scalar (positive affect, CFI = .930, TLI = .920, RMSEA = .077, SRMR = .047; negative affect, CFI = .899, TLI = .884, RMSEA = .077, SRMR = .063) invariance models fit the data well. Importantly, the change in CFI did not exceed .01 in any of the model comparisons, providing evidence for scalar invariance over time. For the

TABLE 1
Means, Standard Deviations, and Zero-Order Correlations

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*
1. Age	—																								
2. Male	.02	—																							
3. Education	−.10	−.10	—																						
4. Married	.27	.02	−.10	—																					
5. Extraversion	−.01	.06	−.02	.04	.77																				
6. Neuroticism	−.14	.11	−.10	−.06	−.16	.75																			
7. Conscientious	.03	.11	.10	.06	.28	−.20	.56																		
8. Agency	−.01	−.12	.12	.01	.52	−.09	.24	.82																	
9. Openness	−.06	−.07	.20	−.07	.52	−.17	.27	.52	.76																
10. Agreeableness	.08	.27	−.09	.04	.53	−.05	.29	.10	.35	.81															
11. W1—PA	.10	−.03	.01	.07	.37	−.49	.24	.22	.21	.20	.91														
12. W1—NA	−.10	.09	−.09	−.07	−.20	.55	−.22	−.14	−.12	−.05	−.63	.86													
13. W1—CC	.18	.12	−.13	.04	−.10	.27	−.13	−.07	−.07	.05	−.32	.41	—												
14. W1—FL	.28	.12	−.22	.05	−.08	.14	−.13	−.04	−.09	.05	−.19	.28	.44	.93											
15. W1—SRH	−.16	−.03	.25	−.02	.16	−.19	.20	.12	.16	.03	.26	−.28	−.41	−.50	—										
16. W2—PA	.14	−.02	.03	.04	.27	−.35	.19	.18	.18	.16	.53	−.38	−.23	−.15	.24	.90									
17. W2—NA	−.11	.09	−.14	−.06	−.12	.40	−.16	−.09	−.08	−.01	−.37	.50	.29	.23	−.26	−.61	.84								
18. W2—CC	.21	.12	−.15	.04	−.04	.19	−.08	−.05	−.05	.06	−.20	.25	.53	.39	−.34	−.26	.40	—							
19. W2—FL	.34	.12	−.23	.09	−.03	.13	−.10	−.04	−.09	.08	−.15	.19	.40	.60	−.40	−.23	.30	.49	.94						
20. W2—SRH	−.18	−.02	.26	−.04	.11	−.16	.18	.09	.14	.01	.19	−.22	−.32	−.39	.53	.29	−.33	−.41	−.55	—					
21. W3—PA	.11	.00	.03	.07	.26	−.31	.19	.16	.15	.17	.47	−.36	−.23	−.16	.25	.59	−.42	−.24	−.20	.25	.91				
22. W3—NA	−.06	.07	−.13	−.06	−.11	.38	−.16	−.10	−.06	−.01	−.34	.44	.31	.23	−.25	−.39	.56	.32	.28	−.27	−.57	.84			
23. W3—CC	.16	.15	−.14	.03	−.07	.21	−.09	−.07	−.06	.08	−.20	.25	.52	.36	−.32	−.23	.30	.58	.44	−.37	−.28	.40	—		
24. W3—FL	.35	.14	−.24	.10	−.02	.13	−.10	−.04	−.09	.11	−.17	.18	.36	.51	−.37	−.17	.22	.41	.66	−.44	−.24	.34	.49	.95	
25. W3 –SRH	−.08	−.02	.23	.00	.09	−.15	.16	.05	.11	.01	.19	−.18	−.30	−.34	.44	.24	−.27	−.36	−.43	.55	.32	−.35	−.44	−.57	—
Mean	46.38	1.52	6.77	.87	3.20	2.24	3.42	2.69	3.02	3.49	3.39	1.54	2.41	1.48	3.53	3.43	1.51	2.46	1.67	3.54	3.44	1.47	3.25	1.85	3.43
SD	13.00	.50	2.49	.34	.56	.66	.45	.66	.53	.49	.73	.62	2.51	.69	.99	.71	.58	2.59	.79	1.02	.72	.58	3.15	.87	1.04

Note: W1 = wave 1, W2 = wave 2, W3 = wave 3, PA = positive affect, NA = negative affect, CC = chronic conditions, FL = functional limitations, SRH = self-reported health. All correlations above .05 are significant at $p < .01$.

TABLE 2
Measurement Invariance across Three Waves for Positive and Negative Affect

	Model	χ^2	*df*	$\Delta\chi^2$ *(df)*	*CFI*	*ΔCFI*	*TLI*	*RMSEA*	*SRMR*
Positive affect	Configural	982.9	114		.933		.910	.085	.036
	Metric	1009.8	124	26.9 (10)	.932	.001	.916	.083	.044
	Scalar	1040.8	134	31.0 (10)	.930	.002	.920	.081	.047
Negative affect	Configural	908.9	114		.903		.870	.082	.062
	Metric	918.6	124	9.8 (10)	.903	.000	.880	.078	.063
	Scalar	965.7	134	47.1 (10)	.899	.004	.884	.077	.063

Note: *df* = degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual.

cross-lagged analyses, the fully constrained model fit the data well as shown in Table 3 based on conventional structural equation modelling fit indices. Specifically, constraining the means (Model 1), lagged (Model 2), cross-lagged (Model 3), or cross-sectional paths (Model 4) did not result in a significant loss in fit (i.e. CFI < .01). Hence, the cross-lagged effects reported in Table 4 were taken from the fully constrained models (i.e. lagged, cross-lagged, and cross-sectional paths were independently constrained to be equal).

The primary focus of this manuscript was to test whether there is a long-term relationship from affect to physical health. We found that, over a 20-year period, positive and negative affect predicted self-reported health (positive affect, $\bar{\beta} = .07$, $p < .05$; negative affect, $\bar{\beta} = -.13$, $p < .05$) and functional limitations (positive affect, $\bar{\beta} = -.09$, $p < .05$; negative affect, $\bar{\beta} = .05$, $p < .05$) in the expected direction. However, neither positive affect ($\bar{\beta} = -.06$, $p > .05$) nor negative affect ($\bar{\beta} = .03$, $p > .05$) significantly predicted future chronic conditions. Regarding the relative strengths of these effects, we found no differences between the magnitudes of these effects. While it appeared that negative affect had a stronger cross-lagged relationship with self-reported health than positive affect and positive affect had a stronger cross-lagged relationship with functional limitations than negative affect, the absolute value of the confidence intervals for these effects overlapped. Specifically, the absolute value confidence interval for negative affect (95% CI, |.07; .18|) predicting future self-reported health overlapped with that of positive affect (95% CI, |.02; .12|) and the same pattern of results was apparent for positive (95% CI, |.04; .14|) and negative affect (95% CI, |.01; .09|) predicting future functional limitations.

We also examined the reciprocal relation between affect and health: does physical health predict future affect? We found that self-reported health predicted both positive ($\bar{\beta} = .13$, $p < .05$) and negative affect ($\bar{\beta} = -.14$, $p < .05$). Further, functional limitations predicted future positive ($\bar{\beta} = -.13$, $p < .05$) and negative affect ($\bar{\beta} = .16$, $p < .05$). However, chronic conditions did not

TABLE 3
Goodness-of-Fit for Random-Intercept Cross-Lagged Panel Model at Various Levels of Constraints in Models of Positive and Negative Affect Predicting Three Health Outcome Variables

	Model	χ^2	*df*	$\Delta\chi^2$ *(df)*	*CFI*	*TLI*	*RMSEA*	*SRMR*
Chronic conditions	Model 0	24.1	7		.999	.984	.019	.008
	Model 1	34.9	13	10.8 (6)	.999	.989	.015	.010
	Model 2	107.0	16	72.1 (3)	.995	.963	.028	.020
	Model 3	111.2	20	4.2 (4)	.995	.970	.025	.021
	Model 4	153.3	26	42.1 (4)	.993	.968	.026	.022
Functional limitations	Model 0	17.0	7		.999	.991	.014	.006
	Model 1	40.7	13	23.7 (6)	.999	.987	.017	.008
	Model 2	105.4	16	64.7 (3)	.996	.965	.028	.019
	Model 3	109.0	20	3.6 (4)	.996	.972	.025	.020
	Model 4	168.2	26	59.2 (4)	.993	.966	.028	.020
Self-reported health	Model 0	25.9	7		.999	.982	.019	.008
	Model 1	37.4	13	11.5 (6)	.999	.988	.016	.010
	Model 2	109.4	16	72.0 (3)	.995	.962	.029	.020
	Model 3	120.7	20	11.3 (4)	.995	.967	.027	.021
	Model 4	163.2	26	42.5 (4)	.993	.965	.027	.021

Note: *df* = degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual.
Model 0: all paths are freely estimated; Model 1: means are constrained to be equal across time for each construct; Model 2: autoregressive lags additionally constrained to be equal within each construct; Model 3: cross-lagged paths between same constructs across time are further constrained to be equal; Model 4: covariance between constructs is constrained to be equal across time.

significantly predict future positive ($\bar{\beta} = -.05$, $p > .05$) or negative affect ($\bar{\beta} = .01$, $p > .05$). We also compared the cross-lagged effects to explore whether affect leading to health was stronger than health leading to affect. For self-reported health, health leading to positive affect was significantly stronger ($\beta_{\text{diff}} = .08$; $p = .001$) than positive affect leading to health; however, there were no differences with respect to negative affect ($\beta_{\text{diff}} = .04$; $p = .135$). Further, functional limitations was a significantly stronger predictor of both positive ($\beta_{\text{diff}} = .07$; $p = .006$) and negative ($\beta_{\text{diff}} = .12$; $p = .000$) affect than the converse. Lastly, we compared whether positive or negative affect was a significantly stronger predictor of future health. We found that positive and negative affect were not significantly different in their prediction of future self-reported health ($\beta_{\text{diff}} = -.06$; $p = .138$) and functional limitations ($\beta_{\text{diff}} = -.03$; $p = .471$). Using *MPlus*, a post-hoc Monte Carlo simulation was conducted to enhance confidence in our results. Two multivariate data sets with all variables in the actual analysis were simulated. The differences between these simulations were the path coefficients. In one simulation, the smallest path coefficients from our results were used as reference—mostly path coefficients from chronic

TABLE 4
Results from Random-Intercept Cross-Lagged Panel Analysis Modelling Affect (Positive and Negative) and Health

	Chronic conditions				*Functional limitations*				*Self-reported health*			
	β	*SE*	*p*	*95% CI*	*β*	*SE*	*p*	*95% CI*	*β*	*SE*	*p*	*95% CI*
Affect → Health												
W1 PA → W2 Health	−.06	.03	.054	−.12; .00	−.09	.02	.000	−.14; −.04	.07	.03	.006	.02; .12
W2 PA → W3 Health	−.06	.03	.054	−.11; .00	−.08	.02	.000	−.13; −.04	.07	.03	.006	.02; .12
W1 NA → W2 Health	.03	.03	.344	−.04; .10	.05	.02	.036	.01; 09	−.13	.03	.000	−.18; −.07
W2 NA → W3 Health	.03	.03	.346	−.03; .09	.05	.02	.037	.01; .09	−.12	.03	.000	−.17; −.07
Health → Affect												
W1 Health → W2 PA	−.05	.03	.079	−.11; .01	−.13	.03	.000	−.18; −.08	.13	.03	.000	.08; .18
W2 Health → W3 PA	−.05	.03	.080	−.11; .01	−.14	.03	.000	−.20; −.08	.13	.03	.000	.08; .18
W1 Health → W2 NA	.01	.03	.758	−.05; .07	.15	.03	.000	.09; .20	−.14	.03	.000	−.19; −.09
W2 Health → W3 NA	.01	.03	.758	−.05; .07	.16	.03	.000	.10; .21	−.14	.03	.000	−.20; −.09
Lagged effects												
W1 PA → W2 PA	.30	.03	.000	.24; .35	.33	.03	.000	.27; .38	.32	.03	.000	.26; .37
W2 PA → W3 PA	.28	.03	.000	.22; .34	.31	.03	.000	.26; .37	.30	.03	.000	.25; .36
W1 NA → W2 NA	.28	.03	.000	.22; .35	.28	.03	.000	.23; .34	.29	.03	.000	.23; .35

Table 4 *(Continued)*

	Chronic conditions				*Functional limitations*				*Self-reported health*			
	β	*SE*	*p*	*95% CI*	β	*SE*	*p*	*95% CI*	β	*SE*	*p*	*95% CI*
W2 NA → W3 NA	.26	.03	.000	.20; .32	.26	.03	.000	.21; .32	.27	.03	.000	.21; .32
W1 Health → W2 Health	.09	.04	.016	.01; .17	.33	.03	.000	.26; .39	.24	.03	.000	.18; .29
W2 Health → W3 Health	.09	.04	.021	.01; .17	.34	.03	.000	.27; .41	.24	.03	.000	.18; .31
Cross-sectional effects												
W1 PA—W1 NA	−.46	.01	.000	−.48; −.44	−.46	.01	.000	−.48; −.44	−.46	.01	.000	−.49; −.44
W1 PA—W1 Health	−.18	.02	.000	−.23; −.14	−.20	.02	.000	−.24; −.16	.23	.02	.000	.19; .26
W1 NA—W1 Health	.24	.02	.000	.20; .29	.23	.02	.000	.19; .26	−.24	.02	.000	−.28; −.20
W2 PA—W2 NA	−.47	.01	.000	−.49; −.45	−.48	.01	.000	−.50; −.45	−.48	.01	.000	−.50; −.46
W2 PA—W2 Health	−.17	.02	.000	−.22; −.13	−.21	.01	.000	−.25; −.17	.23	.02	.000	.19; .27
W2 NA—W2 Health	.25	.02	.000	.20; .29	.25	.02	.000	.21; .29	−.26	.02	.000	−.30; −.21
W3 PA—W3 NA	−.46	.01	.000	−.49; −.44	−.47	.01	.000	−.49; −.45	−.47	.01	.000	−.50; −.45
W3 PA—W3 Health	−.17	.02	.000	−.22; −.13	−.22	.02	.000	−.26; −.18	.23	.02	.000	.19; .27
W3 NA—W3 Health	.25	.02	.000	.20; .30	.26	.02	.000	.22; .30	−.26	.02	.000	−.30; −.22

Note: W1 = wave 1; W2 = wave 2; W3 = wave 3; PA = positive affect; NA = negative affect.

conditions results. In the second, smallest coefficients from the results, excluding chronic conditions, were used. In both simulations, 1,000 trials were run using a random sample of 3,200. Results are reported in Table 5. Using the smallest coefficients yielded poor power; however, results from the second simulation yielded sufficient power—increasing the confidence in our results.

DISCUSSION

Our study suggests that affect matters for certain types of physical health over long periods of time. Specifically, we found that both positive and negative affect uniquely predicted self-reported health and functional limitations. However, neither positive nor negative affect predicted future chronic conditions. Also, although it initially appeared that the relative strength of affect on health depended on the health measurement, we found no difference in the magnitude of these effects. Lastly, our results suggest that there is a reciprocal relation as self-reported health and functional limitations predicted positive and negative affect over time. This is especially meaningful as we adopted a random-intercept cross-lagged panel model (Hamaker et al., 2015), a method used to control for cross-time stabilities and which corrects for potentially inflated cross-lagged parameters.

TABLE 5
Results from Post-Hoc Power Analysis

Relationship	*Parameter estimate*	*Obtained power*
Model 1		
Positive Affect → Future Health	−.03	.38
Negative Affect → Future Health	.03	.40
Health → Future Positive Affect	−.01	.09
Health → Future Negative Affect	.01	.10
Lagged Positive Affect Effects	.26	1.00
Lagged Negative Affect Effects	.26	1.00
Lagged Health Effects	.09	.99
Cross-Sectional Positive Affect-Health Effects	−.17	1.00
Cross-Sectional Negative Affect-Health Effects	.17	1.00
Model 2		
Positive Affect → Future Health	−.05	.82
Negative Affect → Future Health	.05	.84
Health → Future Positive Affect	−.13	1.00
Health → Future Negative Affect	.13	1.00
Lagged Positive Affect Effects	.26	1.00
Lagged Negative Affect Effects	.26	1.00
Lagged Health Effects	.24	1.00
Cross-Sectional Positive Affect-Health Effects	−.23	1.00
Cross-Sectional Negative Affect-Health Effects	.23	1.00

Our research questions centred on whether these effects exist, which our results generally support—despite being relatively small in magnitude. The fact that measures of positive and negative affect predict changes in health a decade in the future (while controlling for both opposite valence affect and current affect) is certainly meaningful. Indeed, similar sized effects have been found in previous research for both affect to health and the health to affect relationships over shorter periods of time (e.g. Finch, Baranik, Liu, & West, 2012). While behaviours more closely tied to an individual's health may yield stronger effects (e.g. Liu et al., 2016), our results suggest that being happier and healthier today may indicate a happier and healthier life 10 years from now.

Concerning the lack of significant chronic condition findings, previous research has shown that positive and negative affect could lead to some chronic conditions such as high blood pressure (Uchiyama, 1992) and stroke (Ostir, Markides, Peek, & Goodwin, 2001), but we did not find that affect predicted future chronic conditions with a cross-lagged model over long periods of time. One possible explanation could be that many of the chronic conditions within the measure are not associated with affect. That is, the chronic conditions measure captures diseases of varying intensity that may or may not be emotionally driven (e.g. asthma, skin trouble, constipation, foot trouble). Specifically, research on this topic has supported the idea that affect may influence emotionally-sensitive health systems (e.g. immune, endocrine, cardiovascular; Yanek et al. 2013); however, our measure of chronic conditions included poor health conditions that may not be driven by affect. For instance, to the best of our knowledge, there is little evidence suggesting that persistent foot trouble may be a downstream consequence of positive/negative affect. Collapsing across different types of health conditions may reduce the effect of affect. Future longitudinal research may seek to further explore the relationship between affect and specific types of chronic conditions.

The results from the current study shed new light on the debate surrounding the relative effects of positive and negative affect on health outcomes. Many believe that the effects of negative affect will be stronger than those of positive emotions (e.g. Baumeister et al., 2001). However, these assumptions have recently been challenged as much of this opinion is based on evidence that does not model positive and negative affect simultaneously (Pressman & Cohen, 2005). Across all three health outcomes, we found that negative affect did not have significantly larger cross-sectional effects (chronic conditions, $\bar{\beta} = .25$, 95% CI, |.20; .29|; functional limitation, $\bar{\beta} = .24$, 95% CI, |.21; .28|; self-reported health, $\bar{\beta} = -.25$, 95% CI, |.21; .29|) than positive affect (chronic conditions, $\bar{\beta} = -.17$, 95% CI, |.14; .22|; functional limitation, $\bar{\beta} = -.21$, 95% CI, |.17; .25|; self-reported health, $\bar{\beta} = .23$, 95% CI, |.19; .27|) nor larger cross-lagged effects on health when compared to positive affect. Hence, these results suggest that positive affect not only matters for health, but also matters just as much as negative affect. These results support the idea that positive and negative affect predict health in unique ways, where negative affect increases the risk of poor health or obstructs positive effects (e.g. Cohen et al., 1993) while positive affect acts to promote good health or mitigate deleterious effects (e.g. Pressman & Cohen, 2005).

Additionally, we found that not only does affect predict future health, but health also predicts future affect. Further, the effect from health to affect seems to be relatively the same as the effect from affect to health. While the majority of studies have examined the affect to health relationship, there is increasing interest in examining the reverse directionality. Health leading to future affect has been demonstrated over much shorter time frames (e.g. Mukuria & Brazier, 2013; Strike, Wardle, & Steptoe, 2004; Wright, Strike, Brydon, & Steptoe, 2005) and the results from the current study provide evidence that this relationship appears to hold over decades. Moreover, these results highlight the importance of the health to affect relationship and support calls for research examining bi-directionality (e.g. Diener et al., 2017). An especially fruitful direction for future research may be examining this bi-directionality over different periods of time. Specifically, the strength of relationship between a leading variable (measured at time 1) and a lagged variable (measured at time 2) may depend on the temporal similarity (i.e. time between measurement occasions), where there is a stronger relationship when there is more temporal similarity.

Limitations

In the present study, we sought to understand the relationship between affect and health using a trait-like valence-based operationalisation of affect. Although this approach allowed us to make general assertions concerning how the valence of affect influences health over 20 years, it also presents some limitations. First, it is possible that distinct positive (e.g. joy, happiness, calm) and negative (e.g. anger, sadness, anxiety) affective states may influence health outcomes differently even when they are of the same valence (Suls & Bunde, 2005). For example, there is increasing evidence that discrete negative affective states may be more indicative of developing coronary heart disease than other similarly valenced states (Kubzansky, Cole, Kawachi, Vokonas, & Sparrow, 2006). There is also evidence that distinct positive affective states influence health differently. Pressman et al. (2017) found that vigour was associated with quality of sleep, whereas calmness was linked to less sleep. Hence, analysis of discrete affective states could provide more insight into the affective underpinnings between affect and health.

Second, affect was conceptualised with respect to valence but not accounting for the degree of affective arousal. The circumplex model (Russell, 1980) suggests that, in addition to the relative pleasantness-unpleasantness of an emotion, affect can be broken down in terms of arousal or intensity. For instance, while stressed, upset, sad, and bored all represent unpleasant emotions, the first two are argued to be more active emotions than the latter two. Given that the health consequences associated with affect are often discussed under the assumption of high arousal (Pressman & Cohen, 2005), it is possible that there may be a more nuanced relationship between the structure of emotional and physical health. Hence, we believe that there should be more research investigating how the structure of affect influences long-term health.

CONCLUSIONS

Given questions of whether affect is associated with physical health over time, our results suggest a nuanced picture. For the outcomes of self-reported health and functional limitations, we find that both positive and negative affect predict future health outcomes, even when they are modelled simultaneously. However, we did not find evidence for affect predicting chronic conditions. We also find that the strength of the relationship between affect and health does not depend upon the valence of affect. Specifically, the relative effects of positive and negative affect predicting health outcomes were of similar magnitudes. This research provides important longitudinal evidence on whether affect is associated with physical health and we hope that it can add to the growing literature on not merely whether affect is related to health in global terms, but whether positive and negative affect similarly contribute to different aspects of physical health over time.

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