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Subjective Well-Being and Health Behaviors in 2.5 Million Americans

Kostadin Kushlev*

Georgetown University, USA

Danielle M. Drummond

University of Utah, USA

Ed Diener

University of Utah, USA

University of Virginia, USA

Gallup Organization, USA

Background: Happiness and health behavior are positively related, but most existing research does not distinguish between conceptually and empirically distinct components of subjective well-being—satisfaction with life, positive affect, and negative affect. **Method:** We assessed the associations of each component of subjective well-being and health behavior, such as exercising and not smoking, in a broad, representative sample of nearly 2.5 million respondents from the USA in the Gallup Daily Poll. **Results:** We found that both life satisfaction and positive affect, but not negative affect, are unique predictors of health behavior, even after controlling for a wide range of variables, including demographics, chronic illness, daily stress and pain, and other relevant factors. Positive affect was linearly related to health behavior, while life satisfaction showed an association only for individuals relatively satisfied with their lives (but not for those dissatisfied with their lives). These associations were not moderated by various factors, occurring across gender and age, personal resources like time and money, and environmental affordances such as access to fresh food and safe places to exercise. **Conclusions:** The relationship between well-being and health behavior is robust and generalisable in a large cross-section of the US population.

Keywords: affect, happiness, health, health behavior, well-being

*Address for correspondence: Kostadin Kushlev, Department of Psychology, Georgetown University, 37th and O Streets, NW, Washington, DC 20057, USA. Email: kk1199@georgetown.edu

Abbreviations
SWB: Subjective Well-Being

PA: Positive Affect

NA: Negative Affect

HBI: Health Behavior Index

INTRODUCTION

Common sense dictates that good health is a necessary, if not sufficient, condition for happiness. In Bulgaria, for example, there is a common saying that goes: "As long as there is health…"; meaning as long as you are in good health, everything else will fall into place. You will be fine, if not happy. Research in psychology, however, tells us that the average person will, eventually, adapt—if not completely recover—after they become sick, lose a limb, or become completely paralysed (Lucas, 2007; Lucas, Clark, Georgellis, & Diener, 2003; Luhmann, Hofmann, Eid, & Lucas, 2012; Wilson & Gilbert, 2003). Thus, while health is undoubtedly a contributing factor to being happy, people might overestimate its causal impact on happiness.

At the same time, researchers who study happiness, or subjective well-being (SWB), have recently begun to discover that happiness matters for health more than people might anticipate. Subjective well-being (Diener, 1984, 2000) consists of a cognitive component, life satisfaction, and two affective components, positive affect (PA) and negative affect (NA). Those with higher well-being are then more satisfied with their lives, have higher levels of PA, and lower levels of NA. Evidence from a growing number of longitudinal, ambulatory, and experimental studies suggests that these facets of subjective well-being are causal factors in better physical health (Diener, Pressman, Hunter, & Delgadillo-Chase, 2017; Lyubomirsky, King, & Diener, 2005). Happier people tend to live longer (Diener & Chan, 2011) and to have better cardiovascular health (Boehm, Vie, & Kubzansky, 2012) and stronger immune systems (Marsland, Cohen, Rabin, & Manuck, 2006). Meta-analyses have confirmed that subjective well-being is, indeed, linked to increased survival in both healthy and ill samples (Chida & Steptoe, 2008), and short-term immune functioning. In one meta-analysis of 150 studies (Howell, Kern, & Lyubomirsky, 2007), the authors concluded that well-being impacts both short-term and long-term health across various objective indicators. Importantly, these researchers were able to statistically isolate the effects of well-being from those of ill-being (e.g. mental illness), concluding that well-being promotes health independently of the detrimental effects of ill-being on health (Howell et al., 2007). Thus, while happiness might be neither a necessary, nor sufficient, condition for good health, you will be more likely to be physically well if you are subjectively well.

Happiness and Health Behavior

As of yet, however, it is unclear *how* greater well-being might lead to better health, or what the mechanisms for these effects could be. Several mechanisms have been proposed, including both direct biological pathways and indirect behavioral pathways, and the effects are likely resultant of some combination of the two (DeSteno, Gross, & Kubzansky, 2013; Steptoe, Dockray, & Wardle, 2009).

Researchers have begun to find empirical support for the proposed behavioral pathways, suggesting that the effects of happiness on health are produced at least in part because happy people engage in more health behaviors, such as being more physically active (Boehm et al., 2012), taking preventative action to mitigate risk (Kim, Kubzansky, & Smith, 2015), and avoiding risky behaviors like not using sun protection (Grant, Wardle, & Steptoe, 2009). While the affective benefits of health behavior such as exercise are widely known, it is likely that well-being and health behavior have reciprocal effects; in other words, exercise makes people feel happier, but happy people may also be more likely to exercise. Indeed, several longitudinal studies have shown that those with greater well-being at baseline engage in more exercise over time (Kim, Kubzansky, Soo, & Boehm, 2017) and show slower declines in fruit and vegetable consumption over time (Boehm et al., 2018). However, this growing literature on the link between happiness and health behaviors has raised almost as many questions as it has answered (Diener et al., 2017).

First, most research has not distinguished between conceptually and empirically distinct components of SWB—satisfaction with life, PA, and NA (Diener, 1984, 2000)—as predictors of health behaviors. Research exploring the emotional components of SWB, for example, has often relied on general mood measures (i.e. feeling good vs. bad), thereby not distinguishing between PA and NA (Diener et al., 2017) and conflating the distinct effects of well-being and ill-being identified in the broader literature on well-being and health (Howell et al., 2007). The role of PA, in particular, has so far received the least support in the literature (Diener et al., 2017). However, the studies that have examined positive and negative affect as separate components suggest that those with more PA have better health, above and beyond the consequences of NA (Pressman, Jenkins, & Moskowitz, 2019). Based on these findings, we might expect individuals with greater PA to also report more engagement in health behaviors, and that this effect would be independent of NA and life satisfaction.

Second, the existing research has not provided a convincing test of the shape of the relationships between each component of SWB and health behavior. Is greater SWB associated with more health behavior in a linear fashion, or is the relationship curvilinear? Outside of the health domain, for example, life satisfaction predicts more active citizenship; however, this relationship is not linear, as people who report extreme satisfaction (10 out of 10) are less likely than more moderately satisfied people to engage in behaviors such as signing a petition or joining a protest (Oishi, Diener, & Lucas, 2007). Would the same be true for health behaviors?

Third, the existing research has not systematically addressed whether the association between SWB and health behavior depends on, or can be explained by, psychological, environmental, and demographic factors. For example, income predicts higher life satisfaction, so wealthier individuals might eat more healthily simply because they can afford to buy fresh food, rather than because they feel better.

To shed light on the key unanswered questions outlined above, we need both a very large and a representative sample. Because the different components of SWB are moderately correlated, large samples are necessary to reliably distinguish between the common and unique variances of these components when predicting health behaviors. A representative sample, in turn, is critical for a convincing examination of the size and shape of the associations, as well as of their possible moderators and confounds. For example, age-restricted samples, such as the students or middle-aged adults commonly used in the existing literature, cannot tell us whether age moderates the associations. In the present research, we examine the associations between components of SWB and health behavior in a large representative sample of the United States with nearly 2,500,000 respondents in the Gallup Daily Poll.

The Present Research

Using a very large and representative sample of the US, we aim to: (a) provide the strongest correlational evidence to date about whether each SWB component is uniquely related to health behavior; (b) characterise the size and shape of these associations; and (c) elucidate any moderating and confounding factors of these associations. By capitalising on the strengths of our very large, representative sample, we overcome key limitations in the majority of existing studies to examine the generalisability of the associations between SWB and health behaviors—across different components and levels of well-being, across different communities, and across various demographic groups. For example, might the association of NA with unhealthy behaviors be due to the common variance of NA with psychological stress or physical pain? Further, is the association between life satisfaction and health behavior due to differences in the availability of resources, such as time, money, and better access to exercise facilities, or does this relationship remain robust even after controlling for these explanatory variables?

METHOD

Participants

We analyse data from the Gallup Daily Poll, consisting of N = 2,478,326 respondents (50% female; 55% married; 81% White, 8% Black, 2% Asian; 8% Hispanic), polled each year between 2008 and 2016 (Medians: Age = 56, Income = \$48,000–\$60,000, Education = "Some College"). Further descriptive and scale information is presented in Table 1.

Procedure

Gallup conducts daily phone interviews of US adults, aged 18 and older, living in all 50 states and the District of Columbia. Both landline and cellphone numbers are sampled using random-digit-dial methods. Gallup stratifies the random-digit-dial samples to ensure that the unweighted samples are proportionate by US Census region and by time zone within region. Landline respondents within each household are chosen at random based on which member has the next birthday. Interviews are conducted in Spanish for primarily Spanish-speaking respondents. More information on the Gallup methodology is available online: https://www.gallup.com/178685/methodology-center.aspx.

Measures

Life Satisfaction. Respondents are asked to evaluate their life using a Cantril Self-Anchoring Ladder (Cantril, 1965)—a well-validated single-item measure of satisfaction with life that is widely used in national and international polls of well-being (Deaton, 2008; Diener, Kahneman, Tov, & Arora, 2010; OECD, 2013). In this measure of life satisfaction, participants imagine a ladder with steps numbered from 0 at the bottom to 10 at the top, where the top of the ladder represents the 10-*best possible life* for them and the bottom of the ladder represents the 0-*worst possible life* for them; participants are then asked: *On which step of the ladder would you say you personally feel you stand at this time?* We used this measure of life satisfaction to operationalise our cognitive, evaluative component of SWB (Deaton, 2008; Diener et al., 2010).

Affect. For the affective components of SWB, participants are asked to report how they felt and what they did on the previous day (i.e. "yesterday"). Thus, participants are asked whether or not (1-*yes*/0-*no*) they *smiled or laughed* during *a lot of the day yesterday* and whether they felt a *sense of enjoyment* during *a lot of the day yesterday*. Following past research (e.g. Helliwell & Wang, 2012; Kahneman & Deaton, 2010), we used these two items to form a composite of positive affect (PA) by averaging the two items, $\alpha = 0.65$. Using the same prompts, participants also reported whether or not they had felt *worry*, *anger*, and *sadness* during *a lot of the day yesterday*. By averaging these three items, we formed our measure of negative affect (NA), $\alpha = 0.62$ (Helliwell & Wang, 2012).[1]

Health Behaviors. Gallup measures four different behaviors to form a *Health Behaviors Index* (*HBI*). First, participants are asked whether or not (1-*yes*/0-*no*) they *ate healthily all day yesterday*, referring to the same day for which participants report their positive and negative feelings. In addition to this general item, participants are asked two additional and more specific questions to assess whether their behavior *over the past week* met current guidelines for healthy eating and physical activity. Thus, they are asked to report *on how many days over the past week*: (a) *They have had five or more servings of fruit and vegetables*; and (b) *Exercised for 30 or more minutes*. Finally, in the fourth item, participants are asked: *Do you smoke?* Unlike the first three items, this fourth item assesses an unhealthy behavior that should be avoided. The four variables correlated with each other as expected (see Table 1). To form the HBI, we reverse-scored smoking and then standardised each of the items before taking their average (Table 1).

Control Variables. In addition to SWB and HBI, we also took advantage of the Poll's inclusion of a wide range of potential confounds and moderators of the SWB–HBI relationship. These included common demographic variables—age, sex, education (highest degree), and income (1 to 10 in progressively larger categories, up to "$120,000+")—as well as a range of other relevant variables about participants' current life circumstances. Participants rated, for example, whether or not (1-*yes*/0-*no*) they experienced *stress* and *physical pain* for *a lot of the day yesterday*. Stress and pain are not typically conceptualised and measured as components of affect (Helliwell & Wang, 2012), but rather as predictors of both positive and negative affect (Diener et al., 2016); stress and pain were thus used as covariates (see Table 1 for descriptives). Participants also responded to a question about whether or not they are currently experiencing any *health problems* that interfere with their usual daily activities. In addition, we also formed an index of chronic illness: We coded whether or not (1 or 0) participants reported having ever been diagnosed with one or more of the following: *asthma*, *diabetes*, *heart attack*, *cancer*, or *other chronic health conditions not listed*. Finally, we included measures of perceived personal resources (e.g. enough money to buy food and time to do desired activities) and various environmental affordances (e.g. a safe place to exercise, or access to affordable fruit and vegetables). Control measures are described in Table 1.

[1] Note that only items included during all waves (years) of the Gallup Daily Poll were included in the composites; thus, happiness (yesterday) was not included in our measure of PA because it was not measured consistently and depression (yesterday) was not included in our measure of NA as it was not measured at all.

TABLE 1
Descriptives and Effect Sizes (Pearson *r* Coefficients) between Subjective Well-Being, Health Behaviors, Demographics, and Controls

	M	*SD*	*min*	*max*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*
1. Life Satisfaction (N)	7.04	1.85	0	10	–																
2. Positive Affect (Y)	0.84	0.32	0-No	1-Yes	0.27	–															
3. Negative Affect (Y)	0.20	0.31	0-No	1-Yes	−0.31	−0.36	–														
4. Not Smoke (N)	0.84	0.37	0-No	1-Yes	0.16	0.08	−0.11	–													
5. Eat Healthily (Y)	0.70	0.46	0-No	1-Yes	0.10	0.12	−0.14	0.08	–												
6. Exercise (W)	2.85	2.46	0 days	7 days	0.09	0.11	−0.07	−0.01	0.13	–											
7. Eat Healthily (W)	4.20	2.53	0 days	7 days	0.09	0.10	−0.06	0.05	0.25	0.20	–										
8. HBI (*z*-score)	0.00	0.58	−2.27	1.68	0.19	0.18	−0.17	0.48	0.63	0.57	0.65	–									
9. Pain (Y)	0.24	0.43	0-No	1-Yes	−0.20	−0.18	0.28	−0.09	−0.05	−0.08	0.00	−0.10	–								
10. Stress (Y)	0.36	0.48	0-No	1-Yes	−0.24	−0.27	0.53	−0.09	−0.17	−0.07	−0.07	−0.17	0.20	–							
11. Chronic Illness (N)	0.44	0.50	0-No	1-Yes	−0.20	−0.18	0.21	−0.07	−0.01	−0.13	0.01	−0.09	0.44	0.12	–						
12. Health problems (N)	0.23	0.42	0-No	1-Yes	−0.11	−0.11	0.13	−0.01	0.01	−0.09	0.01	−0.03	0.25	0.06	0.40	–					
13. Satisfied with living standard (N)	0.78	0.42	0-No	1-Yes	0.46	0.24	−0.32	0.16	0.10	0.06	0.06	0.16	−0.20	−0.26	−0.18	−0.10	–				
14. Enough money for food? (Y)	0.87	0.33	0-No	1-Yes	0.28	0.17	−0.27	0.19	0.09	0.02	0.04	0.15	−0.20	−0.21	−0.18	−0.10	0.36	–			
15. Enough time to get things done? (Y)	0.75	0.43	0-No	1-Yes	0.10	0.14	−0.19	0.02	0.08	0.02	0.00	0.05	−0.11	−0.26	−0.06	−0.03	0.13	0.09	–		
16. Is it easy to get: A safe place to exercise?(N)	0.93	0.25	0-No	1-Yes	0.14	0.14	−0.15	0.07	0.07	0.07	0.03	0.10	−0.12	−0.11	−0.12	−0.07	0.16	0.18	0.08	–	

TABLE 1 *(Continued)*

	M	*SD*	*min*	*max*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*
17. Is it easy to get: fresh fruit/ veggies?(N)	0.93	0.26	0-No	1-Yes	0.14	0.12	−0.15	0.07	0.07	0.01	0.03	0.08	−0.11	−0.12	−0.10	−0.06	0.17	0.19	0.09	0.25	–
19. Sex	–	–	1-M	2-F	0.05	0.01	0.05	0.05	0.01	−0.04	0.13	0.06	0.05	0.04	0.06	0.06	−0.01	−0.06	−0.05	−0.05	−0.05
20. Age	54.30	17.73	18	99+	0.07	0.00	−0.09	0.13	0.25	−0.03	0.14	0.21	0.08	−0.22	0.19	0.26	0.08	0.16	0.10	0.05	0.05
20. Married (or not)	–	–	0-No	1-Yes	0.14	0.08	−0.09	0.13	0.03	0.00	0.03	0.08	−0.06	−0.03	−0.09	−0.05	0.10	0.15	−0.04	0.07	0.05
21. Education	3.97	1.56	1	6	0.14	0.07	−0.07	0.18	−0.01	0.04	0.02	0.10	−0.12	0.02	−0.13	−0.06	0.11	0.19	−0.07	0.09	0.06
22. Annual Income	6.66	2.32	1	10	0.26	0.12	−0.16	0.17	−0.02	0.03	0.01	0.08	−0.18	−0.04	−0.22	−0.13	0.25	0.32	−0.04	0.14	0.12

Note: Cases excluded pairwise. N_{total} = 2,478,326; HBI = Health Behavior Index; T = Today; Y = Yesterday; W = Past Week; N = Now, in general. Income categories: 1 (under \$720) to 10 (\$120,000+) in progressively larger categories. Education categories: 1 (less than high-school), 2 (high-school or equivalent), 3 (vocational school), 4 (some college), 5 (college graduate), 6 (post graduate work or degree).

Analytic Strategy

We first examined the bivariate correlations between each component of SWB and each of the health behaviors (see Table 1). We then tested whether the relationships can be explained by a wide range of control and demographic variables in a series of regression analyses (see Table 2). For parsimony, we focused on the composite measure of health behavior (HBI) in these analyses. In each case, we use correlation coefficients as our standardised measure of effect size. Because in such a large sample, effects of negligible size can be highly significant, we draw on guidelines by Cohen (1988) to interpret effect sizes as small (r = 0.10), medium/moderate (r = 0.20), or large (r = 0.50). We highlight effects that reach a size of at least r = 0.10.

Finally, because this threshold is fundamentally arbitrary, we also employ a nonparametric machine learning technique to determine whether each SWB component contributes unique predictive power over and above other SWB components and a range of controls. This exploratory approach—Multiple-Adaptive Regression Splines, or MARS (Friedman, 1991)—allowed us to test for higher-order, curvilinear relationships, as well as all combinations of interactions between the predictors. Starting from the intercept-only model, MARS first adds multiple combinations of the specified predictors to the model—including their linear, quadratic, and higher polynomial terms—until error in the outcome is no longer substantially reduced (i.e. R^2-change < 0.001). To prevent overfitting, MARS supplements this forward method with a backward method, whereby terms deemed unlikely to generalise beyond the given data are consecutively removed until the most parsimonious and generalisable model is achieved. Because MARS does not rely on statistical significance to determine the best model, it is a particularly useful technique for supplementing parametric testing (based on p-levels) when working with a very large sample such as ours. Importantly, in addition to testing multiple configurations of variables, MARS models not only the linear but also the curvilinear effects for each variable by including ever higher polynomial terms for each predictor, and estimating the exact breakpoints in the curve. Unlike parametric piecemeal regression models, where the number of breakpoints is user-specified, MARS effectively "adapts" to the data in order to model the specified relationship as a series of segmented lines that best fit the data. This allows us to test the implicit assumption in our more traditional regression models that health behavior is linearly related to components of SWB.[2]

[2] We used listwise deletion of cases in these analyses to ensure that our results are not due to the particular imputation technique—mean replacement—employed in the traditional regressions presented in Table 2.

RESULTS

Bivariate Associations

We found that three components of SWB were moderately correlated with the overall index of health behaviors (Table 1). Zooming in on the bivariate correlations of each SWB component with each health behavior, people who evaluated their lives more positively were less likely to smoke. In contrast, people who experienced negative emotions were more likely to smoke. NA was most strongly predictive of not having eaten healthily on the previous day. In general, however, PA seemed more consistently predictive of approach-oriented health behaviors over the past week, such as eating five servings of fruit and vegetables or exercising for at least 30 minutes a day. This pattern of correlations gives initial credence to the idea that life satisfaction, PA, and NA may have distinct associations with health behaviors. In general, NA seems more strongly related to unhealthy behaviors like smoking, whereas PA seems to predict health-promotive behaviors. Despite the distinguishable patterns with specific health behaviors, the correlations of the three SWB components with the HBI composite were remarkably similar. Table 1 also shows the expected moderate relationships between life satisfaction, PA, and NA. Finally, we decomposed the variance in the relationships due to differences in means between counties and differences in means between individuals within counties[3] (using *StatsBy* function in package *psych* 1.8.10 in *R* 3.5.1). These analyses revealed that the amount of variance due to between-county differences was very small, *ICCs* < 0.02. Indeed, the pooled within-county correlations were virtually identical to the full correlations presented in Table 1.

Linear Regressions

To explore whether each component of SWB uniquely predicts health behavior, we turn to Table 2 where we present the results of a series of linear regression models. Effect sizes are presented as partial correlation coefficients. In Model 1, we predicted HBI simultaneously from life satisfaction, PA, and NA. As shown in Table 2, both life satisfaction and PA continued to predict health behavior with rs > 0.10. Overall, SWB explained $R^2 = 0.060$, or 6 per cent of the variance in the health behavior index. While also significant, the predictive power of NA was more substantively diminished, falling below the threshold for a small effect size, $r < 0.10$. Because the majority of our health behaviors composite consists of actively engaging in positive health behavior (e.g. exercising and

[3] County was inferred from the self-reported zip code of the respondent.

eating well) rather than not engaging in negative behaviors (e.g. smoking), these results are consistent with the general pattern of correlations we saw in Table 1.

In Model 2, we added several related, but distinct, variables that could further explain the relationship between SWB and HBI. First, given the more pronounced relationship between NA and smoking, it is possible that its remaining common variance with the HBI composite was due to stress. Indeed, including how stressed people felt yesterday, *r-partial* = −0.083, b(se) = −0.115(0.001), $\Delta R^2 = 0.006$, further reduced the relationship between NA and HBI, *r-partial* = −0.032, b(se) = 0.073(0.001), but had little effect on the shared variance of HBI with PA, *r-partial* = 0.104, or life satisfaction, *r-partial* = 0.118. In Model 2 (Table 2), we also added the number of acute and chronic health issues, reasoning that they may function as a third factor causing people both to feel less happy and to take less care of their health. Experiencing pain on the previous day, or suffering from a more chronic health condition, such as diabetes or heart disease, displayed negligible relationships with HBI (Table 2). Overall, the three control variables in Model 2 explained an additional variance of $\Delta R^2 = 0.007$, or less than 1 per cent.

In Model 3, we added 11 more predictors. In addition to common demographic controls—age, sex, marital status, education, and income—we included variables characterising people's current environment and life circumstances that are particularly likely to influence both SWB and HBI (see Table 2). Overall, these variables explained an additional variance of $\Delta R^2 = 0.05$, or 5 per cent. Including this wide range of variables did reduce, but did not completely explain, the shared variance between health behaviors and life satisfaction (Table 2). PA, however, remained a remarkably robust predictor of health behavior, $r > 0.10$. Of these 16 additional predictors, age was the only variable other than PA that reached an effect size of $r > 0.10$: Older people reported greater engagement in health behavior, such as eating their vegetables and doing their exercises.

Finally, we explored whether our demographic variables—age, sex, marital status, education, and income—moderate the relationships between each SWB component and the health behavior index. Building on Model 3, we added the interaction terms of all three SWB components with each of the five demographic variables. These 15 interaction terms added very little additional predictive value to the model, $R^2 = 0.118$, compared to Model 3, $\Delta R^2 = 0.001$. The strongest effect was for the interaction between age and life satisfaction, which was of negligible effect size, *r-partial* = 0.02. We explore moderation in more detail next with MARS.

MARS Exploration

A notable strength of the present research is our reliance on a representative sample of over two million Americans. But this very strength makes it difficult for

TABLE 2
Regressions Predicting the Health Behavior Index (HBI) from Subjective Well-Being, Stress, Chronic Health Issues, Demographics, and Other Factors

	R^2	*F (df)*		*Raw* $r_{partial}$	*Imputed* $r_{partial}$	*Imputed* B	*Imputed* β	*Imputed* *95% CI Lower*	*Imputed* *95% CI Upper*
Model 1	0.060	52730 (3, N)	Intercept			−0.444		−0.447	−0.441
			Life Satisfaction	**0.128**	**0.124**	**0.042**	**0.130**	**0.041**	**0.042**
			Positive Affect	**0.110**	**0.112**	**0.218**	**0.119**	**0.216**	**0.221**
			Negative Affect	−0.077	−0.078	−0.160	−0.084	−0.162	−0.157
Model 2	0.067	29680 (6, N)	Intercept			−0.386		−0.389	−0.382
			Life Satisfaction	**0.119**	**0.116**	**0.039**	**0.121**	**0.038**	**0.039**
			Positive Affect	**0.102**	**0.103**	**0.202**	**0.110**	**0.200**	**0.205**
			Negative Affect	−0.028	−0.028	−0.065	−0.034	−0.068	−0.062
			Stress	−0.081	−0.081	−0.113	−0.094	−0.115	−0.112
			Felt Pain	−0.025	−0.025	−0.036	−0.026	−0.037	−0.034
			Chronic Illness	0.010	0.010	0.012	0.010	0.010	0.013
Model 3	0.117	19250 (17, N)	Intercept			−0.985		−0.991	−0.978
			Life Satisfaction	0.064	0.071	0.025	0.077	0.024	0.025
			Positive Affect	**0.101**	**0.103**	**0.199**	**0.108**	**0.196**	**0.201**
			Negative Affect	−0.017	−0.018	−0.040	−0.021	−0.043	−0.038
			Stress	−0.041	−0.047	−0.066	−0.054	−0.068	−0.064
			Pain	−0.012	−0.015	−0.022	−0.016	−0.024	−0.020
			Chronic Illness	−0.018	−0.027	−0.033	−0.028	−0.034	−0.031
			Health problems preventing normal activities?	−0.037	−0.038	−0.059	−0.043	−0.061	−0.058
			Satisfied with own standard of living?	0.032	0.026	0.046	0.027	0.044	0.048

TABLE 2 *(Continued)*

R^2	F (*df*)		Raw	*Imputed*				
			$r_{partial}$	$r_{partial}$	B	β	*95% CI Lower*	*95% CI Upper*
		Enough money for food?	0.011	0.019	0.036	0.020	0.034	0.038
		Enough time to get things done yesterday?	−0.011	−0.008	−0.013	−0.008	−0.015	−0.011
		Is it easy to get: A safe place to exercise?	0.034	0.030	0.076	0.029	0.073	0.079
		Is it easy to get: Affordable fresh fruit/veggies?	0.012	0.011	0.027	0.011	0.024	0.030
		Sex	0.056	0.059	0.066	0.057	0.065	0.068
		Age	**0.185**	**0.185**	**0.006**	**0.195**	**0.006**	**0.007**
		Married (or not)	0.037	0.035	0.042	0.035	0.040	0.043
		Education (highest degree)	0.074	0.068	0.026	0.069	0.025	0.026
		Annual Income	−0.014	−0.009	−0.003	−0.009	−0.003	−0.003

Note: All coefficients are significant at $p < .001$. Bolded predictors indicate $r_{\text{partial}} > 0.10$, highlighting effects reaching at least small effect size. To keep sample consistent across models, we imputed missing values by the mean substitution method. The effect size (*r*-partial) for the raw, unimputed data are provided for comparison, indicating negligible differences in effect size due to imputation. R^2 was equivalent to R^2-adjusted in all models. $N = 2{,}478{,}308$.

us to clearly define whether a predictor is uniquely associated with health behavior because virtually all predictors are significant with so much statistical power. Machine-learning statistical methods provide a solution to this problem, allowing us to efficiently explore various configurations of variables to determine whether a given predictor contributes unique predictive power. We thus employ Multiple-Adaptive Regression Splines, or MARS (Friedman, 1991), enabling us to maximise the predictive power of the model without including any unnecessary variables.

As seen in Table 3, the results of the MARS models are remarkably consistent with those from the parametric regressions, while revealing further details about the shape of the relationships. Model 1 confirms our conclusion that all three components of SWB are independently associated with health behavior, with each improving the predictive power of the model (Figure 1). As before, life satisfaction was the most important predictor, followed by PA, and then NA (see Table 3). Model 2 from MARS also replicates the traditional regression results, suggesting that stress adds even more predictive power to the model, but pain, health problems, and chronic illness do not (Table 3; for graphic representation of the results see Figure S1 in the Supplementary Online Materials). In Model 3, we again see that life satisfaction and PA maintain predictive power, even after including nine additional controls. Only age was a stronger unique predictor of health behavior than life satisfaction and positive affect. Negative affect, however, again carried no unique predictive importance in this model (Table 3; Figure S1).

Interestingly, life satisfaction in these models remained a stronger predictor than PA—unlike in the earlier linear regressions where, in Models 2 and 3, PA demonstrated a stronger linear relationship to health behaviors than life satisfaction. Examining the plots in Figure 1, it is easy to see that the source of this discrepancy might be that life satisfaction is better characterised by a curvilinear relationship with health behavior. Thus, while PA shows a largely linear relationship to health behaviors, life satisfaction is positively related to eating better, exercising more, and smoking less primarily for people who are moderately to very satisfied with their lives. We also see that the association with age is mostly due to a progressive increase in health behavior for people over 49 years old, with virtually no relationship for people below that age (see Table 3). The exact shapes of the best-fitting relationships are presented in Figure 1 (Model 1) and Figure S1 (Models 2–3). In sum, our machine-learning models confirm that the variance health behavior shares with life satisfaction and PA is robust to controlling for a wide range of explanatory variables.

Moderation. Finally, we reran Model 3 a second time, allowing for two-way interactions between all 17 predictors. Thus, if the effects of PA, NA, and life satisfaction depend on one another, or on one of the other 14 variables, MARS would include this interaction term in the model. These analyses allowed

TABLE 3
Machine Learning Models Predicting Health Behavior (HBI) Based on Multiple-Adaptive Regression Splines (MARS)

	Type	R^2	*Predictor Importance*	*Chosen Predictors*	B
Model 1	Additive	0.065	1	Life Satisfaction > 6.28	0.073
				Life Satisfaction < 6.28	0.003
			2	Positive Affect > 0.5	0.200
				Positive Affect < 0.5	0.257
			3	Negative Affect > 0.33	−0.124
				Negative Affect < 0.33	−0.212
Model 2	Additive	0.071	1	Life Satisfaction > 6.28	0.069
				Life Satisfaction < 6.28	0.003
			2	Stress	−0.109
			3	Positive Affect > 0.5	0.186
				Positive Affect < 0.5	0.241
			4	Negative Affect > 0.67	−0.105
				Negative Affect < 0.67	−0.076
			Dropped	Pain	
			Dropped	Chronic Illness	
			Dropped	Health problems preventing normal activity?	
Model 3	Additive	0.119	1	Age > 49	0.010
				Age < 49	0.002
			2	Life Satisfaction > 6.29	0.048
				Life Satisfaction < 6.29	0.002
			3	Positive Affect > 0.5	0.206
				Positive Affect < 0.5	0.211
			4	Education > "Some College"	0.061
				Education < "Some College"	0.012
			5	Health problems preventing activity?	−0.080
			6	Stress	−0.007
			7	Married (or not)	0.061

TABLE 3 *(Continued)*

	Type	R^2	*Predictor Importance*	*Chosen Predictors*	B
			8	Sex (Female)	0.063
			9	Is it easy to get: A safe place to exercise?	0.097
			Dropped	Negative Affect	
			Dropped	Pain	
			Dropped	Chronic Illness	
			Dropped	Satisfied with own standard of living?	
			Dropped	Enough money for food?	
			Dropped	Enough time to get things done yesterday?	
			Dropped	Is it easy to get: Affordable fresh fruit/veggies?	
			Dropped	Annual Income	
Model 3	Interactive	0.120	10	Education × Satisfied with Standard of Living	0.038

Note: Model 1: N_{sample} = 2,375,413; $N_{\text{predictors}}$ = 3 entered; N_{terms} = 6 selected;
Model 2 : N_{sample} = 2,368,953; $N_{\text{predictors}}$ = 6 entered; N_{terms} = 7 selected;
Model 3 (Additive): N_{sample} = 806,002; $N_{\text{predictors}}$ = 17 entered; N_{terms} = 13 selected;
Model 3 (Interactive): N_{sample} = 806,002; $N_{\text{predictors}}$ = 17 entered; N_{terms} = 14 selected; $N_{\text{2-way terms}}$ = 163 possible.

us to see whether observed associations between SWB and HBI generalise across various groups or depend on other factors. For example, we reasoned that the availability of accessible fresh food or safe exercise facilities should moderate a relationship between SWB and health behavior. As in the regressions, we found little evidence that this interactive model improved upon the additive Model 3, explaining only ΔR^2 = 0.001 in additional variance. The single interaction that slightly improved the model was between two of the control variables: education and satisfaction with one's standard of living (Table 3). People with less education who were unsatisfied with their standard of living were less likely to engage in health behavior (Figure S1).

DISCUSSION

In a nationally representative sample of over two million participants, we found that life satisfaction and positive affect (PA) are both unique independent predictors of health behavior. Amongst the three components of subjective well-being (SWB), PA was the only one to demonstrate robustness to alternative explanations and variables, while also demonstrating a linear relationship with health behavior. For example, PA was a stronger and more robust predictor of daily health behavior than negative affect (NA), whose common variance with the health behavior index (HBI) seemed to be explained by stress and, even further, by demographics and the current conditions of one's life. As the negative effects of ill-being on health have been well established (e.g. Suls & Bunde, 2005), our pattern of findings is somewhat surprising (Diener et al., 2017). Our findings are consistent, however, with meta-analytic findings showing that well-being promotes health independently of the detrimental effects of ill-being on health (Howell et al., 2007). The more people smile, laugh, and enjoy themselves, the more likely they are to exercise, eat well, and stay away from smoking.

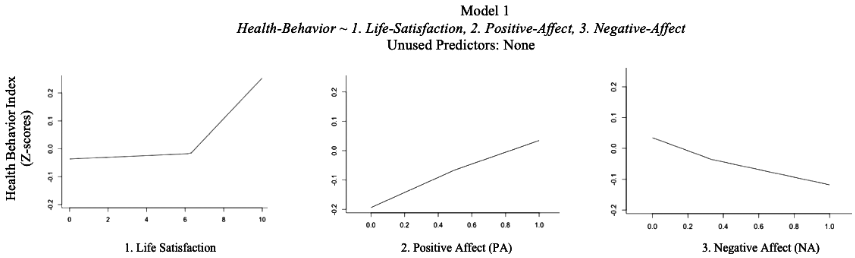

FIGURE 1. Life satisfaction, positive affect, and negative affect uniquely predict health behavior based on Multiple-Adaptive Regression Splines (MARS). Unique predictors are identified based on the additive predictive power of each predictor (R^2 > 001) over and above the other predictors. Selected predictors are shown in order of predictive importance. Higher-order polynomial relationships, allowed for all predictors, are represented as a series of segmented lines that best fit the data.

The strength of the relationships we observed between SWB and health behavior was in the range of statistically small effect sizes (i.e. $r = 0.10$; Cohen, 1988). Although the bivariate relationships of each SWB component with health behavior were closer to $r = 0.20$, only PA still predicted health behavior at $r > 0.10$ after controlling for a range of possible confounds. In fact, PA was a stronger unique predictor of following healthy lifestyle guidelines—to exercise, to eat well, or to avoid smoking—than all but one of the control variables, including being in pain or under stress, having money and access to healthy food and exercise facilities, and even battling chronic illness and having health problems interfering with the activities of daily life. The only control variable that explained more variance than PA—approximately three times as much—was age.

Interestingly, the relationship of one's overall life satisfaction to health behavior was not as linearly related to these health behaviors as PA during even a single day. The critical point that characterised this curvilinear relationship of life satisfaction with health behavior was approximately the midpoint of the scale. Thus, our findings show that there is no difference in health behavior between people who evaluate their lives as very bad versus those who see their lives as only moderately satisfying. People who are very satisfied with their lives, however, do tend to follow a healthier lifestyle than those who are only moderately satisfied. Since the Cantril Ladder approximates a semantic differential scale—anchored so that low scores capture dissatisfaction and high scores indicate satisfaction—these findings suggest a possibly larger association of health behavior with life satisfaction than with life dissatisfaction. Taken together with the robust association of health behavior with PA, but not with NA, these findings cautiously suggest that well-being is a better predictor of health behavior than ill-being.

Our large representative sample also allowed us to explore possible moderators of the relationship between SWB and health behavior. Surprisingly, across a wide range of variables, we found no evidence that these relationships depended on factors that included demographic characteristics, medical history, the availability of personal resources (e.g. money for food), and even relevant affordances of the local environment (e.g. safety and access to exercise facilities). Together with the mounting evidence from longitudinal and experimental studies that well-being does make people behave more healthily (Diener et al., 2017), our findings suggest that such causal relationships may exist not despite inauspicious circumstances, but precisely because happier people are driven to overcome whatever hurdles to a healthy lifestyle they may face. More research is necessary to explore whether motivation, among other factors, may mediate the relationship between well-being and health behavior.

Limitations

One limitation of the present research is that, while we employed a large and representative US sample, it is unclear whether these results might generalise to other countries or regions of the world. A second limitation—inherent in daily national polling of the entire US—is that the measures gathered by Gallup are brief, including fewer items typically used in composite measures of SWB in the psychological literature. Emotional well-being was assessed using dichotomous measures that ask participants to report whether or not they felt a limited set of emotions at all during the preceding day. More precise measures of affect such as the Day Reconstruction Method (DRM; Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004) have recently become available in representative samples, such as the American Time Use Survey (ATUS) and the German Socioeconomic Panel (G-SOEP; Wagner, Frick, & Schupp, 2007). Future research should thus explore whether the pattern of effect sizes we observed would replicate with more precise measures of affect (cf. Kushlev, Dunn, & Lucas, 2015). Relatedly, meta-analytic reviews should compare the effect sizes we observed here with those obtained from more well-established, validated scales of affect, such as the Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988) or the Scale of Positive and Negative Experience (SPANE; Diener et al., 2010).

Third, while past research has suggested a causal role of well-being in health and health behavior (for review, see Diener et al., 2017), another limitation of the present study is that its cross-sectional nature precludes us from making claims of causality. As previous research has suggested reciprocal effects of health and well-being (e.g. DeSteno et al., 2013; Steptoe et al., 2009), it is entirely plausible that individuals who engage in health behavior become happier as a result. Thus, we believe that the relationships we observed between well-being and health behaviors are almost certainly due, in part, to an effect of health behavior on well-being. This reverse direction of causality is particularly important to note for the health behaviors that people reported over the week prior to reporting their well-being (exercising and consuming fruit and vegetables). This timing of measurement issue, however, does not seem to be the whole story here, as we did observe relationships between health behaviors, such as eating healthily, measured for the same day as positive and negative affect (see Table 1). Still, the present research neither attempts to nor is capable of providing evidence of causality.

Implications

If the present findings say nothing about the causal effects of well-being on health behavior, then what is the value of these findings? First, our correlational findings should be interpreted in the context of the existing causal evidence for an effect of SWB on health (for a review, see Diener et al., 2017). In that context, our research contributes to the advancement of knowledge by characterising the correlational link between well-being and health in a large, representative sample. Thus, a key contribution of our findings is in characterising the size of the statistical relationships between SWB and important health behaviors.

Second, whether or not SWB causes health behaviors, we can confidently state that SWB predicts health behaviors, explaining more than 6 per cent of the variance. In fact, above and beyond a wide range of psychological, situational, and demographic factors, SWB predicted an additional 1–2 per cent of the variance in health behavior. This means that national polls of well-being—such as those becoming increasingly available through Gallup, ATUS, or the G-SOEP—may improve predictive models aiming to identify populations at greater risk for health issues due to poor physical activity, diet, or bad health habits. Put simply, the present research documents the unique predictive value of well-being—however brief and imprecise its measurement—for health behavior, adding further evidence that subjective well-being is a unique indicator of a healthy nation (cf. Diener, 2000).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure S1. Machine learning models predicting health behavior (HBI) based on Multiple-Adaptive Regression Splines (MARS): Unique predictors are identified based on the additive predictive power of each predictor (R^2 > 001) over and above the other predictors. Selected predictors are shown in order of predictive importance. Higher order polynomial relationships, allowed for all predictors, are represented as a series of segmented lines that best fit the data.