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WHAT ARE THE MOST IMPORTANT PREDICTORS OF SUBJECTIVE WELL-BEING? INSIGHTS FROM MACHINE LEARNING AND LINEAR REGRESSION APPROACHES ON THE MIDUS DATASETS

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Introduction

Subjective well-being (often abbreviated as well-being or SWB) can be broadly defined as frequent positive emotions, infrequent negative emotions, and satisfaction with one's life (Diener, 1984), in whatever manner they may be reached for a particular individual. Uncovering the best methods for achieving well-being has been the life project of numerous philosophers, theologians, scientists, and laypeople. Most scientific work in this area uses randomized controlled trials (RCTs) in which participants are randomly assigned to different manipulations. The assumption underlying RCTs is that any observed differences between individuals in different experimental conditions can be causally attributed to the manipulated variables rather than confounding variables. However, given the resources required to conduct RCTs, research on the causes of well-being (see Bolier et al., 2013, for a review) has much to gain by rank ordering its *possible* causes, so that future RCTs may prioritize particular predictors over others (see Diener et al., 2018). Furthermore, an important part of identifying the most promising candidates for RCTs is identifying interaction effects. Many researchers have hypothesized strong interaction effects among predictors of SWB, but nothing like a comprehensive list has been generated. Here, we attempt to provide such exploratory foundations for future RCTs by applying both linear regression and advanced machine learning (ML) algorithms to assess the relative strength of and interactions between an extensive array of possible predictors of well-being in a large open-source dataset.

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The Strongest Predictors of Well-Being

Diener (1984) defined SWB as comprising two components—affective (i.e., positive affect and negative affect) and cognitive (i.e., life satisfaction). The origins of SWB research can be traced back to correlational methods (for reviews, see Diener, 1984; Wilson, 1967), and several decades of research have identified a long and diverse set of lists of well-being correlates (Diener et al., 2018). Meta-analyses have reviewed these lists and identified some of the stronger correlates of well-being. For example, Lyubomirsky and her colleagues (2005) found that aspects of sociability, likability, prosocial behavior, and positive perceptions of oneself and others were most predictive of well-being. Although such meta-analyses may yield insights into which constructs are strong predictors of SWB (see Table 6.1 for a list of constructs and their meta-analytic correlations with well-being), they cannot directly establish the relative strength of predictors or interaction effects because meta-analyses combine results from different types of studies and populations. Indeed, the meta-analyses presented in Table 6.1 used a variety of well-being measures (e.g., life satisfaction vs. positive affect) and were conducted on a variety of populations (e.g., older adults vs. college students).

TABLE 6.1 Meta-Analytic Correlations with Well-Being

Construct	*Meta-Analytic Correlation*	*Citation*
Meaning in Life	0.47	Pinquart (2002)
Self-Compassion	0.47	Zessin, Dickhäuser, and Garbade (2015)
Neuroticism	−0.46	Anglim, Horwood, Smillie, Marrero, and Wood (2020)
Optimism	0.43	Alarcon, Bowling, and Khazon (2013)
Extraversion	0.37	Anglim, Horwood, Smillie, Marrero, and Wood (2020)
Sociability	0.37	Lyubomirsky, King, and Diener (2005)
Conscientiousness	0.36	Anglim, Horwood, Smillie, Marrero, and Wood (2020)
Prosocial Behavior	0.35	Lyubomirsky, King, and Diener (2005)
Mindfulness	0.34	Giluk (2009)
Self-Esteem	0.31	DeNeve and Cooper (1998)
Leisure Engagement	0.26	Kuykendall, Tay, and Ng (2015)
Agreeableness	0.25	Anglim, Horwood, Smillie, Marrero, and Wood (2020)
Competence	0.21	Pinquart and Sörensen (2000)
Openness	0.19	Anglim, Horwood, Smillie, Marrero, and Wood (2020)
Household Income	0.18	Howell and Howell (2008)
Physical Health	0.14	Howell, Kern, and Lyubomirsky (2007)
Religiosity	0.10	Hackney and Sanders (2003)

Accordingly, although each construct as defined in its respective study has been shown to correlate with well-being at the strength listed in Table 6.1 (e.g., $r = 0.47$ for meaning in life and $r = 0.37$ for sociability), we cannot infer from that table that Meaning in Life is a stronger correlate of well-being than Sociability generally.

A study that seeks to make the relative comparisons implied by Table 6.1 must overcome several challenges. First, predictors of SWB are correlated to a considerable degree with one another. For example, the Big Five traits are related to a host of other variables (e.g., prosociality, self-esteem, and health), which are also mutually related to SWB (Ozer & Benet-Martínez, 2006). As such, effect sizes between predictors of SWB are difficult to compare due to the difficulty in discriminating their unique contributions. Second, predictors of SWB may interact with one another. For example, it is possible that the effect of sociability on SWB depends on gender or on levels of agreeableness. With so many predictors of SWB, many interaction effects are possible. Obtaining data to exhaustively test those interactions is difficult because the dataset would need to include many predictors and a large enough sample to reliably detect interaction effects. Third, predictors of SWB may relate to well-being in nonlinear ways. For example, the association between income and SWB appears to be nonlinear (Caporale et al., 2009). Fourth, estimates of predictors' effect sizes often come from different studies that span a range of different methods or populations. Thus, if the correlation between meaning and well-being in one set of studies is higher than the correlation between gratitude and well-being in another, one cannot conclude that meaning is a stronger correlate of well-being than gratitude, as the strengths of these correlations are impacted by the methods used in each study.

The Role of ML in Identifying Predictors

We can more effectively interrogate the strength and interaction of predictors of well-being by comparing the performance of linear regression with advanced ML algorithms on a single large dataset. The extent to which more complex models (e.g., ML models and regression models with product terms) are more predictive of SWB than simpler regression models (e.g., linear ridge regression) reflects the extent to which predictors relate to SWB in nonlinear and interactive ways. Comparing model performance on a single large dataset that measures multiple predictors of SWB eliminates the challenges inherent in comparing data derived from disparate outcome measures and populations. By analyzing one such large dataset with a combination of linear regression and advanced ML algorithms, we ultimately aim to rank order predictors of SWB and uncover nuances (i.e., interactions, nonlinearity) in how those predictors influence well-being.

Current Project

Using the nationally representative Midlife in the United States (MIDUS) datasets, the current project seeks to take advantage of recent methodological advances in ML to (1) establish the relative importance of predictors of SWB and (2) evaluate the extent to which predictors relate to SWB in nonlinear and interactive ways. To our knowledge, no previous study has examined a set of predictors of well-being as relevant and as broad as those in the MIDUS datasets or used ML techniques to identify whether predictors in such a dataset relate to well-being in nonlinear or interactive ways.

Method

Participants

The first MIDUS data collection project (MIDUS 1) gathered data in 1995 and 1996 using the University of Wisconsin Survey Center. A sample of adults living in the U.S. was recruited primarily using random digit dialing. In 2004 and 2005, this sample was re-recruited (with a response rate of 69.8%) and assessed again on similar measures (MIDUS 2). In 2011–2014, a new sample (MIDUS R) was collected, with similar measures to MIDUS 2. MIDUS R was sampled independently of MIDUS 2 (no re-recruitment), and again consisted of U.S. adults recruited primarily through random digit dialing.

We obtained all the data from the MIDUS 2 and MIDUS R datasets, then cleaned the data based on two criteria. First, some participants were recruited as siblings or twins of a participant or as part of designed oversampling of urban areas. These participants were excluded from our analyses to achieve a highly representative sample of U.S. adults. The remaining sample consisted of 2,257 adults from MIDUS 2 and 3,577 adults from MIDUS R (5,834 unique individuals). Second, participants were excluded if they had missing data on over 200 items (out of 855 total items). This approach resulted in a final sample of 4,378 unique adults in total from the MIDUS 2 and MIDUS R datasets.

The participants in the final sample ranged in age from 23 to 84 years old (M = 54.1, SD = 13.8). Of these participants, 87% were White, 54% were female, 64% were employed, 66% were married, 76% were Christian, 97% were heterosexual, and 44% had a bachelor's degree, according to self-reports of these demographic characteristics.

Procedure and Measures

Participants first responded to questions via a telephone interview and were then sent $25. One week later (ten days later for MIDUS R), participants were sent a self-administered questionnaire, instructions, a tape measure for body measurements, $10, and a business reply envelope to send back the complete self-administered questionnaire. When the self-administered questionnaires were received, the participant was mailed $25.

For a list of items used, please see the Supplemental Material available at our OSF link (https://osf.io/c453s/?view_only=2be486917daf4523ab186dbaff8c5609) and the MIDUS documentation available at Radler (2014).

Data Cleaning

Creating a Target: Subjective Well-being

The target for this analysis was SWB, which is typically defined as a combination of high positive affect (PA), low negative affect (NA), and high life satisfaction (LS) (Diener, 1984). One might expect that PA, NA, and LS would be related to the features in our dataset in different ways, thereby warranting three separate analyses, one for each construct. However, we were interested in a holistic measure of well-being and therefore ultimately opted to combine these constructs into a single evaluation of the participant's subjective experience. The best way of accomplishing this is a matter of some debate, but in this study, we formed a composite SWB score by averaging PA, NA (reverse scored), and LS in a manner similar to previous research (Diener, 1984; Sheldon & Elliot, 1999; Sheldon & Lyubomirsky, 2006).

Positive and negative affect were measured with 13 and 14 items, respectively. Participants were asked how much of the time they felt certain emotions during the past 30 days on a 5-point Likert scale. The positive emotions included cheerful, in good spirits, happy, calm, satisfied, full of life, close to others, belonging, enthusiastic, attentive, proud, active, and confident. Negative emotion items included sad, nervous, restless, hopeless, everything being effortful, worthless, lonely, afraid, jittery, irritable, ashamed, upset, angry, and frustrated. Composites of positive and negative affect were created by averaging each set of items.

A life satisfaction composite was formed by standardizing (i.e., z-scoring) and then averaging one item and two composites. The life satisfaction item asked participants the extent to which they were satisfied with life at present on a 4-point Likert scale. A life rating composite was formed by averaging three items asking participants to rate their present life, life ten years ago, and life ten years in the future using an 11-point Likert scale. A self-acceptance composite was calculated by averaging seven items from the self-acceptance sub-scale of the Psychological Well-Being Scale (Ryff & Keyes, 1995), which were answered using a 7-point Likert scale. The life satisfaction item, life rating composite, and self-acceptance composite were standardized and then averaged to form a life satisfaction composite. The self-acceptance items were considered measures of life satisfaction because disattenuated correlations between self-acceptance and measures of life satisfaction have been found to be 0.95 or greater (Margolis et al., 2019).

An SWB composite was calculated by standardizing and then averaging the positive affect, negative affect (reverse scored), and life satisfaction composites. Using the standardized loadings from a one-factor exploratory factor analysis of the 38 SWB items, ω_t equaled 0.96. The SWB composite described above correlated with a composite where all items were weighted equally (i.e., simply averaged) at $r = 0.97$.

Creating Trait Features

The other items of the MIDUS surveys were scored into traits (i.e., trait features) using item averages. Some traits consisted of just one item, but most traits consisted of several items (with 748 items forming 189 traits). The items comprising each trait are listed in the Supplemental Material available at our OSF link (https://osf.io/c453s/?view_only=2be486917daf4523ab186dbaff8c5609).

Item transformations. All items were transformed before forming trait composites. First, categorical items were dichotomized (e.g., combining the few homosexual and bisexual participants into one "not heterosexual" group). Some variables featured high positive skew because they were count variables. For example, one item asked about the number of hours per month one spends volunteering at a hospital. These highly positively skewed count variables were log-transformed (base 10) after adding 1 to the variable (to prevent values of negative infinity). Next, some items were multiplied by -1 (i.e., reverse-coded) so that higher scores on the associated trait indicated higher levels of that construct. Lastly, all items were standardized to have a mean of 0 and variance of 1.

Excluded items. Items were not used to form traits if they met any of the six conditions. First, items were removed if they had a high proportion of missingness, which occurred in two situations. If an item was present in one survey but not the other, the item would have a high proportion of missingness. In addition, some items simply had low response rates, often because they were not applicable to the participant sample (e.g., most people could not provide the age at which they had a heart attack, because most people had not had a heart attack). Items that had more than 500 missing cases were removed. Second, we removed two items that did not have any variance. Third, any variable that was calculated or determined from other variables was removed, as this was redundant with averaging items into traits. Fourth, items tautologically related to SWB were removed (following imputation, described below). These items either concerned mental health, were labeled as measures of well-being in the MIDUS documentation, or asked participants to rate how well the previous day or month went. However, the subscales of the Psychological Well-Being Scale (e.g., environmental mastery and purpose in life) were included as they are not tautologically related to SWB. Indeed, some argue that eudaimonic constructs, such as those assessed with the Psychological Well-Being Scale, are best seen as causes, rather than constituents, of well-being (Sheldon, 2018). Fifth, some items that simply seemed far more specific than other trait-level variables and could not be formed into a composite were removed (e.g., whether one would prefer a coronary bypass or medication to solve a heart issue). Sixth, some items were redundant with other items. For example, because three items concerned blood pressure, two of the three items with the least specific response options were removed.

Trait labels. Traits were labeled as "subjective" or "objective." All traits were assessed via self-report, and thus all were subjectively reported. However, some traits regarded subjective ratings (e.g., rating the strength of one's financial situation using a Likert scale), whereas others regarded more objective characteristics (e.g., estimating income).

Creating Objective and Subjective Domain Features

To further reduce the dimensionality of the data, we generated composites of the traits, called domains. Based on the content of the objective traits, 17 objective domains were formed. These domains were created by averaging traits within a domain, but some domains consisted of one trait (e.g., female status) and thus were not averaged. The subjective traits were entered into an exploratory factor analysis using the minimum residual method and oblimin rotation. A scree plot suggested 11 factors (see Figure 6.1). Furthermore, the loadings of these 11 factors produced interpretable factors. Thus, 11 subjective domain factor scores were extracted, resulting in a total of 28 total subjective and objective domains. As a result, in total, we ended up with 748 items forming 189 traits, which were then reduced to 28 domains.

Creating Weak Features

It is possible that a simpler linear regression model may outperform an ML model when testing the strongest predictors that explain most of the variance (as long as the effects are largely linear). In order to determine if the model performance differentiates only among weaker predictors, we created datasets of weak traits and weak domains. The goal was to select the traits (or domains) that were most weakly associated with SWB. We selected the weakest features such that a Lasso regression model predicting SWB from these features would have a nested cross-validation multiple R of approximately 0.50. To create a dataset of weak traits, we removed all traits with a correlation above 0.15 in magnitude with SWB. When the remaining 80

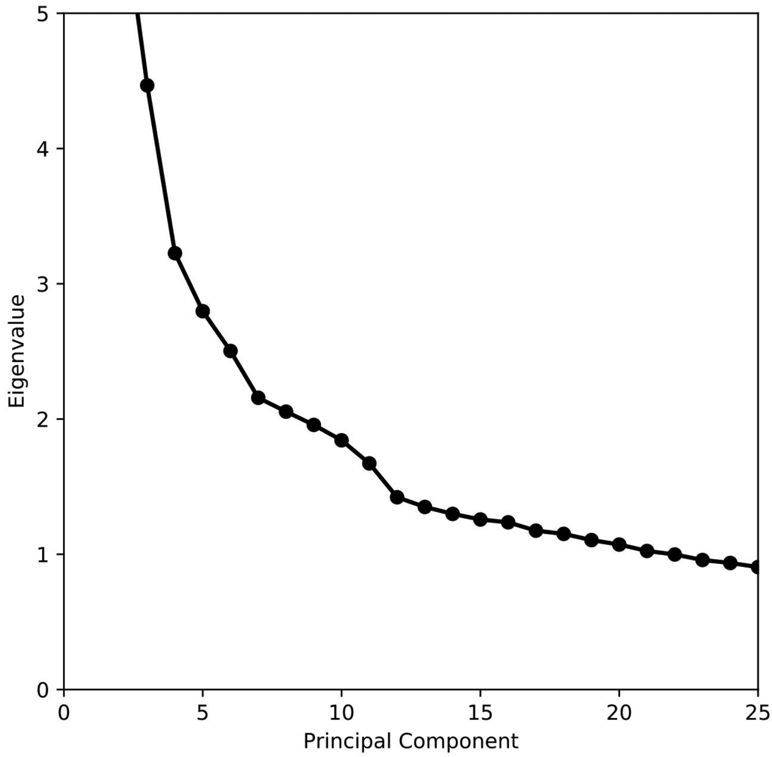

FIGURE 6.1 Scree plot of subjective traits. Eigenvalues of components 1 and 2 are greater than 5.0.

features were used to predict SWB in a Lasso regression model, the nested cross-validation multiple R was 0.50. To create a dataset of weak domains, we removed all traits with a correlation above 0.22 in magnitude with SWB. When the remaining 15 features were used to predict SWB in a Lasso regression model, the nested cross-validation multiple R was 0.49.

Feature Selection

The performance of ML models is often reduced, rather than unchanged, by the inclusion of features that are not predictive of the target when the other features are included in the model (e.g., see John, Kohavi, & Pfleger, 1994). Thus, for trait, domain, weak trait, and weak domain datasets, we removed features if their regression coefficient in a Lasso regression model was zero.

For all four of the above datasets (trait, domain, weak trait, and weak domain datasets), we created three additional datasets: one with squared features in addition to the untransformed (i.e., linear) features, one with untransformed and product features, and one with untransformed, squared,

TABLE 6.2 Lasso Regression Results

Features	*Squares*	*Products*	*Coefficients equal to 0*	*Coefficients not equal to 0*	*α*
Traits	No	No	82	106	0.0065
Traits	Yes	No	219	129	0.0085
Traits	No	Yes	17469	297	0.0171
Traits	Yes	Yes	17633	293	0.0171
Domains	No	No	4	24	0.0034
Domains	Yes	No	10	43	0.0034
Domains	No	Yes	317	89	0.0119
Domains	Yes	Yes	313	118	0.0096
Weak Traits	No	No	12	68	0.0060
Weak Traits	Yes	No	34	126	0.0058
Weak Traits	No	Yes	2998	242	0.0240
Weak Traits	Yes	Yes	3057	263	0.0232
Weak Domains	No	No	0	15	0.0002
Weak Domains	Yes	No	0	28	0.0027
Weak Domains	No	Yes	45	75	0.0107
Weak Domains	Yes	Yes	55	78	0.0115

Note. All features datasets included untransformed features. α = α hyperparameter.

and product features. Thus, we created 16 datasets in total. We used Lasso regression to perform feature selection on each dataset. See Table 6.2 for results of these lasso regression models and see Table 6.3 for a list of subjective domains with representative items from those domains.

Based on a Lasso regression model, a range of features was removed from the trait dataset. Previous research does not identify many of these features as important predictors of SWB. However, some important exceptions include objective chronic pain, objective health limitations, subjective generativity, subjective pessimism, and subjective religiosity. Many of these features are likely to be at least somewhat predictive of SWB, but they failed to predict SWB over and above the other selected features. The same possibility applies to the features removed from the domain dataset: objective employment status, objective giving and receiving, and subjective resilience.

Statistical Techniques

Brief overviews of each statistical technique are provided in this section. Ridge regression without squared or product terms was our baseline for linear, non-interactive prediction of SWB. Support vector regression was used to

TABLE 6.3 Example Items of Subjective Domains

Domain	*Item*
Subjective Control	How would you rate the amount of control you have over your life overall these days?
Subjective Physical Health	In general, compared to most men/women your age, would you say your health is…
Subjective Disengagement	When I experience a stressful event, I give up trying to reach my goal.
Subjective Sociability	I usually like to spend my leisure time with friends rather than alone.
Subjective Socioeconomic Status	I feel safe being out alone in my neighborhood at night.
Subjective Sex Life	How would you rate the sexual aspect of your life these days?
Subjective Societal Evaluation	The world is becoming a better place for everyone.
Subjective Social Dominance	Please indicate how well assertive describes you.
Subjective Prosociality	How much thought and effort do you put into your contribution to the welfare and well-being of other people these days?
Subjective Religiosity	How religious are you?

identify nonlinear effects. Random forests and artificial neural networks were used as different approaches to identifying both nonlinear and interactive effects. Increased predictive capability of support vector regression, random forests, and/or artificial neural networks is interpreted as indicating the presence of nonlinear and/or interaction effects within our SWB predictors. Steps were taken to reduce model overfit and bias, explained below and expanded upon in the Results. For the interested reader, more detail on all statistical techniques is provided in the Appendix stored at our OSF link (provided earlier).

Results

Summary of Model Comparisons

None of the machine learning models significantly outperformed ridge regression. The ML models did show marginal improvement over ridge regression with untransformed features, suggesting some weak nonlinear and interaction effects. This pattern was corroborated by improved performance of ridge regression models when including product and squared terms. But again, the improvements were only marginal, implying that the predictors of well-being included in this analysis are largely linear and non-interactive.

Efforts were made to avoid overfitting the ML models on training data by utilizing k-fold cross-validation with grid search and nested cross-validation to tune and select hyperparameters. Even so, the stated performance of the advanced machine learning models may be somewhat optimistic. Therefore, the lack of any significant predictive improvement by the advanced machine learning models over linear ridge regression is even more notable, further supporting the assertion that the predictors of SWB within the MIDUS dataset are largely linear and non-interactive.

Two other interesting patterns emerged from the model comparisons. First, when attempting to model nonlinear and interactive effects, ridge regression with transformed features generally performed slightly better than the ML models. Second, the ML models generally performed better on weak domains compared to all other features, although interactive effects in particular were more evident within traits compared to within domains.

Ranking Predictors of Subjective Well-Being

Table 6.4 presents the list of traits and how strongly they predict SWB. We report correlation coefficients as r, ridge regression coefficient as β_R, and random forests importance as *RF*. Most traits exhibited an adequate degree of internal consistency (as measured by ω_t) to interpret correlations, regression coefficients, and importance values from random forest models. Generally, these metrics agreed on which trait features were most predictive of SWB. However, the ridge regression coefficients and random forest importances were more similar to each other than either were to the correlations, which likely occurred because, unlike correlations, the former two metrics statistically control for other features. When compared with objective traits, subjective traits tended to be more predictive of SWB. Indeed, of the 30 most predictive traits, only aches was objective (r = –0.47, β_R = –0.07, *RF* = 0.03).

Unsurprisingly, the theorized correlates of psychological well-being—such as environmental mastery (r = 0.74, β_R = 0.13, *RF* = 0.14), purpose in life (r = 0.63, β_R = 0.06, *RF* = 0.14), and positive relations with others (r = 0.57, β_R = 0.05, *RF* = 0.05)—were among the traits most predictive of SWB. In contrast, the strongest negative association with SWB was subjective stress reactivity (r = –0.56, β_R = –0.08, *RF* = 0.05), providing useful insight into potential detriments or barriers to SWB. Another intuitive result was that ratings of physical health (r = 0.50, β_R = 0.05, *RF* = 0.03), work situation (r = 0.49, β_R = 0.04, *RF* = 0.03), and financial situation (r = 0.49, β_R = 0.04, *RF* = 0.03) were highly predictive of SWB. Perhaps more interestingly, ratings of control in one's life– such as control over life (r = 0.57, β_R = 0.11, *RF* = 0.06), control over work situation (r = 0.43, β_R = 0.02, *RF* = 0.01), control over health (r = 0.42, β_R = 0.02, *RF* = 0.01), and a general sense of autonomy (r = 0.37, β_R = –0.01, *RF* = 0.01)—were highly associated with

TABLE 6.4 Trait Results

Trait	ω_t	r	*Ridge Regression Coefficient*	*Random Forest Importance*
Subjective Environmental Mastery	0.80	0.74	0.13	0.14
Subjective Self Esteem	0.81	0.71	0.15	0.13
Subjective Purpose in Life	0.79	0.63	0.06	0.08
Subjective Control Over Life Rating		0.57	0.11	0.06
Subjective Positive Relations with Others	0.79	0.57	0.05	0.05
Subjective Stress Reactivity	0.74	−0.56	−0.08	0.05
Subjective Optimism	0.70	0.54	0.04	0.03
Subjective Physical Health	0.83	0.50	0.05	0.03
Subjective Work Situation Evaluation	0.63	0.49	0.04	0.03
Subjective Financial Situation Evaluation	0.79	0.49	0.04	0.03
Objective Aches	0.77	−0.47	−0.07	0.03
Subjective Health Compared to Others Same Age	0.73	0.46	0.03	0.02
Subjective Sleep Issues	0.82	−0.45	−0.05	0.02
Subjective Standing in Community		0.44	0.03	0.01
Subjective Personal Mastery	0.75	0.44	−0.00	0.01
Subjective Control Over Work Situation		0.43	0.02	0.01
Subjective Control Over Health		0.42	0.02	0.01
Subjective Home Quality	0.81	0.42	0.01	0.01
Subjective Social Integration	0.76	0.42	0.01	0.01
Subjective Extraversion	0.77	0.41	0.05	0.01
Subjective Home Work Rewarding	0.71	0.41	0.03	0.01
Subjective Life Control		0.41	0.04	0.01
Subjective Alienation	0.62	−0.41	0.01	0.00
Subjective Disappointed by Achievement		−0.40	−0.06	0.01
Subjective Self Protection	0.75	0.39	0.02	0.01
Subjective Coping Positive Reinterpretation	0.81	0.37	0.02	0.00
Subjective Autonomy	0.72	0.37	−0.01	0.01

(*Continued*)

TABLE 6.4 (Continued)

Trait	ω_t	r	*Ridge Regression Coefficient*	*Random Forest Importance*
Subjective Social Contribution	0.71	0.36	–0.01	0.00
Subjective Coping Venting Emotion	0.82	–0.35	–0.03	0.01
Subjective Life Effort Rating		0.34	0.02	0.00
Subjective Intellectual Aging	0.74	–0.34	0.01	0.00
Subjective Conscientiousness	0.70	0.33	–0.01	0.00
Subjective Family Strain	0.80	–0.33	–0.02	0.01
Objective Short Breath	0.79	–0.33	–0.02	0.00
Objective Daily Spiritual Experiences	0.89	0.33	0.05	0.01
Subjective Coping Active	0.75	0.33	–0.01	0.00
Objective Visits to Health Professionals	0.55	–0.33	–0.07	0.01
Subjective Coping Behavioral Disengagement	0.75	–0.33	0.01	0.00
Subjective Daily Discrimination	0.92	–0.32	–0.02	0.00
Subjective Family Support	0.85	0.32	0.01	0.00
Subjective Planning for Coping	0.84	0.31	–0.00	0.00
Subjective Social Closeness	0.70	0.31	0.02	0.00
Subjective Sex Life Evaluation	0.79	0.31	0.04	0.01
Subjective Health Compared to Five Years Ago	0.85	0.29	0.04	0.01
Subjective Control Contribution to Others Rating		0.29	–0.01	0.00
Subjective Health Locus of Control	0.73	0.29	–0.01	0.00
Subjective Friend Support	0.88	0.28	0.01	0.00
Subjective Contribution to Others		0.28	0.02	0.00
Objective Sleep Issues	–0.28		–0.02	0.00
Subjective Social Coherence	0.50	0.27	–0.00	0.00
Subjective Openness to Experience	0.77	0.26	–0.01	0.00

(*Continued*)

TABLE 6.4 (Continued)

Trait	ω_t	r	*Ridge Regression Coefficient*	*Random Forest Importance*
Subjective Social Potency	0.73	0.25	–0.02	0.00
Objective Could Not Get Healthcare		–0.24	–0.02	0.00
Subjective Selective Secondary Control	0.63	0.24	–0.01	0.00
Subjective Foresight		0.24	–0.01	0.00
Subjective Somatic Amplification	0.55	–0.23	–0.03	0.01
Subjective Compensatory Primary Control	0.75	0.23	0.01	0.00
Objective Digestion Issues	0.49	–0.22	–0.01	0.00
Subjective Agreeableness	0.80	0.22	–0.03	0.00
Subjective Friend Strain	0.81	–0.21	–0.01	0.00
Objective Alcohol Issues	0.80	–0.20	–0.02	0.00
Subjective Religious Coping	0.83	0.20	0.01	0.00
Objective Neighborhood Contact	0.73	0.20	0.01	0.00
Subjective Live for Today	0.65	–0.19	0.01	0.00
Objective Married		0.19	0.04	0.00
Objective Age		0.17	0.04	0.00
Objective Health Procedures	0.69	–0.17	–0.01	0.00
Objective Sleep Time	0.66	–0.17	–0.02	0.00
Objective Drug Use	0.68	–0.16	–0.02	0.00
Objective Others Alcohol Use	0.18	–0.16	–0.01	0.00
Objective Brain Issues	0.47	–0.16	0.02	0.00
Objective Receiving Money	0.39	–0.16	–0.01	0.00
Subjective Health Locus of Control Others	0.11	–0.15	0.02	0.00
Objective Religious Activity	0.87	0.15	0.01	0.00
Objective Drug Problem		–0.14	–0.02	0.00
Objective Heart Issues	0.74	–0.14	0.01	0.00
Subjective Mental Stimulation	0.51	0.14	–0.02	0.00
Subjective Weight Perception		–0.13	0.01	0.00
Objective Time Volunteering	0.40	0.13	–0.01	0.00
Objective Highest Education Completed		0.13	–0.01	0.00
Objective Tobacco Use	0.58	–0.13	–0.02	0.00

(*Continued*)

TABLE 6.4 (Continued)

Trait	ω_t	r	*Ridge Regression Coefficient*	*Random Forest Importance*
Subjective Financial Situation Effort		0.13	−0.02	0.00
Objective Healthcare Place Doctors Office		0.13	0.01	0.00
Objective Others Tobacco Use	0.31	−0.12	−0.01	0.00
Subjective Important to Help People		0.12	−0.01	0.00
Subjective Control	0.66	0.12	−0.01	0.00
Subjective Religious Mindfulness	0.95	0.12	−0.01	0.00
Objective Grandparent		0.11	0.01	0.00
Objective Mental Health Groups	0.81	−0.10	0.01	0.00
Objective Heterosexual		0.10	0.01	0.00
Objective Years in State		0.09	0.02	0.00
Subjective Spirituality	0.92	0.09	−0.02	0.00
Subjective Insight into Past	0.39	0.09	−0.02	0.00
Objective Number Children		0.09	0.00	0.00
Objective Hips Size		−0.08	0.01	0.00
Objective Medical Exams	0.43	0.08	0.01	0.00
Subjective Explore Different Religions		−0.07	−0.01	0.00
Objective Caregiving		−0.07	−0.02	0.00
Objective Receiving Physical Assistance	0.56	−0.07	0.01	0.00
Objective Lived in Institution		−0.06	0.01	0.00
Objective Diabetes		−0.05	0.02	0.00
Objective Most Seen Healthcare Professional		0.05	0.01	0.00
Subjective Traditionalism	0.60	0.04	0.01	0.00
Subjective Sympathy	0.53	0.04	−0.01	0.00
Objective White		0.03	0.01	0.00
Objective Currently Pregnant		0.03	0.02	0.00

Note. ω_t = omega total. *r* = correlation. ω_t values are not displayed for traits that consisted of one feature, as ω_t cannot be calculated in that case. Propensity Simple Coefficient = regression coefficient in a model where only the feature is predicting subjective well-being using inverse probability of treatment weighting. Propensity Multiple Coefficient = regression coefficient in a model where all trait features predict subjective well-being using inverse probability of treatment weighting.

SWB. In addition, paralleling previous findings, SWB was highly related to subjective ratings regarding social interactions—for example, social integration (r = 0.42, β_R = 0.01, RF = 0.01), extraversion (r = 0.41, β_R = 0.05, RF = 0.01), and social contribution (r = 0.36, β_R = –0.01, RF = 0). By contrast, demographic factors—such as pregnancy (r = 0.03, β_R = 0.02, RF = 0) and ethnicity (r = 0.03, β_R = 0.01, RF = 0)—showed among the weakest associations with SWB. Although a trait labeled "subjective control" was weakly associated with SWB (r = 0.12, β_R = –0.01, RF = 0), this trait reflects control in the sense of cautiousness and constraint.

Table 6.5 displays the list of domains and how strongly they predict SWB. Mirroring the results with traits, subjective domains were generally more predictive of SWB than objective traits were, with objective physical health

TABLE 6.5 Domain Results

Domain	*r*	*Ridge Regression Coefficient*	*Random Forest Importance*
Subjective Control	0.68	0.36	0.33
Subjective Physical Health	0.64	0.21	0.20
Subjective Disengagement	–0.55	–0.22	0.14
Subjective Sociability	0.47	0.19	0.09
Objective Physical Health Issues	–0.40	–0.07	0.03
Subjective Socioeconomic Status	0.32	0.03	0.02
Subjective Sex Life	0.31	0.09	0.02
Subjective Societal Evaluation	0.28	0.05	0.02
Objective Financial Situation	0.26	0.01	0.01
Objective Religious Activity	0.25	0.05	0.02
Objective Human Contact	0.24	0.01	0.01
Subjective Social Dominance	0.22	0.07	0.01
Objective Drug Use	–0.22	–0.07	0.01
Subjective Prosociality	0.21	–0.08	0.01
Objective Marital Status	0.19	0.06	0.00
Subjective Religiosity	0.18	0.04	0.01
Objective Age	0.17	0.08	0.01
Objective Others Drug Use	–0.17	–0.02	0.01
Objective Sleep	–0.17	–0.04	0.01
Objective Health Treatment	–0.16	–0.05	0.01
Objective Education	0.13	–0.01	0.00
Objective Physical Size	–0.12	0.02	0.01
Objective Physical Activity	0.10	0.01	0.01
Objective Female Status	0.05	0.00	0.00

Note. r = Pearson's correlation. Propensity Simple Coefficient = regression coefficient in a model where only the feature is predicting subjective well-being using inverse probability of treatment weighting. Propensity Multiple Coefficient = regression coefficient in a model where all domain features predict subjective well-being using inverse probability of treatment weighting.

issues being an exception. In addition, subjective evaluations of control ($r = 0.68$, $\beta_R = 0.36$, $RF = 0.33$), physical health ($r = 0.64$, $\beta_R = 0.21$, $RF = 0.2$), and sociability ($r = 0.47$, $\beta_R = 0.19$, $RF = 0.09$) were strongly associated with SWB. However, domain-level analyses led to some insights that were not clearly visible at the trait level. For example, disengagement (e.g., withdrawing from a stressful event) ($r = -0.55$, $\beta_R = -0.22$, $RF = 0.14$), judgments of socioeconomic status ($r = 0.32$, $\beta_R = 0.03$, $RF = 0.02$), and subjective evaluations of one's sex life ($r = 0.31$, $\beta_R = 0.09$, $RF = 0.02$) were all important predictors of SWB. Financial situation ($r = 0.26$, $\beta_R = 0.01$, $RF = 0.01$), religious activity ($r = 0.25$, $\beta_R = 0.05$, $RF = 0.02$), and human contact (i.e., the frequency and duration of time spent socializing with friends, family, etc.) ($r = 0.24$, $\beta_R = 0.01$, $RF = 0.01$) were among the most predictive objective domains. Once again, demographic factors, such as education ($r = 0.13$, $\beta_R = -0.01$, $RF = 0$) and gender ($r = 0.05$, $\beta_R = 0$, $RF = 0$), were among the weakest predictors of SWB.

Discussion

What are the most important sources of well-being? The present research aimed to shed some light on that question by leveraging the large open-source MIDUS dataset to investigate the relative strength of various predictors of well-being. Our goal was to inform future RCTs investigating causal influences on well-being by identifying strong predictors and interaction effects. Corroborating previous work (see below), we found that social relationships and subjective physical health were among the strongest predictors of well-being, and we found new evidence suggesting that control over one's life may be among those strongest predictors as well. Surprisingly, however, we did not find any strong evidence of interaction effects (e.g., that the effect of physical health depended on religious activity, or that the effect or sociability depended on socioeconomic status). Our results consistently showed that simpler models limited to linear effects (e.g., multiple regression) performed approximately as well as advanced ML models, and that including nonlinear and interactive effects in regression models improved their prediction only nominally. In other words, predictors of well-being appear to be largely non-interactive in this dataset.

Predictors of Subjective Well-Being

The majority of our findings vis-à-vis particular predictors of SWB match those found in the literature. For example, prior research has revealed high associations between SWB and previously theorized components or correlates of psychological well-being, such as interpersonal relationships, self-esteem, and purpose in life (DeNeve & Cooper, 1998; Ryff, 1989), satisfaction with particular areas of life (Rojas, 2006), sociability (Cooper et al., 1992; Oishi et al., 2007), physical health (Diener et al., 2017), disengagement (Wrosch et al., 2003), sex life (Markmann et al., 2021), wealth (Diener & Biswas-Diener, 2002), and religious activity (Tay et al., 2014). Moreover, the finding that subjective stress reactivity and disengagement from stressful events are the strongest negative associations (for trait and domain predictors, respectively) with SWB is consistent with developmental (Engel & Gunnar, 2020) and health (McEwen & Stellar, 1993) research relating individual differences in susceptibility to stress with maladaptive mental health and physical health outcomes. We also found that most demographic factors were poor predictors of SWB, consistent with previous research in the U.S. (Diener, 2000; Lyubomirsky, Sheldon, et al., 2005; Sheldon & Lyubomirsky, 2021). Moreover, self-reported physical aches was interestingly the only objective predictor in the 30 most predictive traits (Graham et al., 2011; Mukuria & Brazier, 2013).

In sum, the findings of this project are consistent with previous meta-analytic work on predictors of SWB and build on that work with new results clarifying relative effect sizes. As illustrated in Table 6.1, meaning, neuroticism, optimism, and extraversion have been found in meta-analyses to be among the strongest predictors of well-being, a finding replicated on this dataset. However, we also found that self-esteem and physical health were stronger predictors of SWB than suggested by previous meta-analyses. Recall that meta-analyses are generally not well-suited to establishing relative effect sizes, and our use of an expansive set of possible predictors within the same large sample combats some of the relevant limitations of meta-analytic approaches.

The most notable finding regarding effect sizes was the strength of the association between control and SWB. Although previous research suggests that autonomy, or sense of control (see self-determination theory; Deci & Ryan, 2012; see also Bandura, 1999; (Maier & Seligman, 1976) and locus of control (i.e., whether events in one's life are determined by one's actions versus external factors) are critical to well-being ((Lu et al., 2001; Lu & Shih, 1997), most previous research considers other factors as even more important. For example, autonomy and control are hardly mentioned in a recent review of SWB research (Diener et al., 2018). That a sense of control was the strongest predictor of SWB at the domain level highlights the importance of investigating this construct in future correlational and intervention research.

Detecting Nonlinear and Interaction Effects on Subjective Well-Being

We expected ML models to be more effective in predicting SWB relative to linear regression due to the complexity of the problem, multicollinearity of the predictors, and the high dimensionality of the data. Additionally, we expected that predictors would depend on one another (i.e., interact) and exhibit nonlinear associations with SWB. However, the results of the models revealed that only a small proportion of the variance in SWB can be explained by nonlinear and interaction effects. This is not to say that identifying the small proportion of variance explained by interactive and nonlinear effects is unimportant, but rather, that much of the variance in SWB can be identified by assumptions of linearity and a lack of dependence (i.e., interaction), especially for broader domains (i.e., composites).

Although the nonlinear and interaction effects were small, some interesting patterns within them nevertheless emerged. At the domain level, it appeared that more complex ML models (i.e., support vector regressions and artificial neural networks) predict SWB approximately as well as, or sometimes marginally better than, ridge regression models with squared and product terms. However, when using the traits and weak traits features, these ML models did not fit as well as the simpler ridge regression model with squared and product terms. Moreover, nonlinear and interaction effects appeared to the greatest extent in the trait-level datasets, although they were simple enough to capture with merely product and squared terms in linear regression models. For data with the strongest nonlinear and interaction effects, such as the trait-level datasets, ML models did not fit as well as a model that predicted SWB as a linear combination of features, given that those features include squared and product terms. The differences between traits and domains in nonlinearity and interactive effects may be partially explained by the fact that composite scores that are aggregated measures of multiple covarying indicators are generally more reliable and predictive (Diamantopoulos et al., 2012; Nunnally & Bernstein, 1994) and attenuate errors that are inherent in single indicators (DeVellis, 2003). It is possible that the more granular trait-level datasets exhibit nonlinear and interactive effects reflective of (1) error or (2) distinct trait-level associations that are attenuated in the domain-level composites. A recommendation for future SWB investigators attempting to identify linear and non-interactive effects may be to maximally reduce sets of possible covarying predictors to a single composite or principal factor. Conversely, if one is specifically interested in nonlinearity and interactive effects, we caution against averaging or performing dimensionality reduction on possible predictors, as this may limit the ability to identify nonlinear associations and interactions.

Limitations and Future Directions

Although the MIDUS datasets are larger, more representative, and include more measured variables than most datasets used in psychology, they are not without limitations. First, MIDUS was collected in the United States, and thus findings from this project may not generalize to other countries and cultures. For example, control may be a weaker predictor of well-being in countries that are more interdependent than the United States (Lachman &

Weaver, 1998). Second, even a sample size of 4,378 is small for most ML tasks. With a larger sample, complex effects may become more reliable (i.e., persist under cross-validation), and the ML models may reveal more insights than those found with the current dataset.

Third, although the MIDUS datasets included many possible predictors of well-being, some constructs important for well-being were not measured (e.g., gratitude and work productivity). A study with all constructs relevant to SWB, although quite costly, would likely include a longer list of constructs that are important predictors of SWB.

Finally, all measures were obtained via self-report. We labeled some measures as "objective" because they attempted to measure objective quantities (e.g., hours spent helping a family member). However, even these measures are likely impacted by self-report biases (e.g., socially desirable responding, extreme responding, and acquiescence). In addition, because all measures were assessed via self-report, the associations between features and SWB are likely inflated due to the presence of common method variance.

Concluding Thoughts

SWB is a complex and multifaceted construct. As such, when attempting to explain all the possible variance in this construct, it seems reasonable to assume that a substantial proportion of the variance would consist of nonlinear and interactive relationships. Indeed, previous research has identified nonlinear relationships between well-being and age (Blanchflower & Bryson, 2021) and income (Yu & Wang, 2017). Other studies have identified the presence of interaction effects, such as poor well-being outcomes for high neuroticism (vulnerable) narcissists relative to low neuroticism (grandiose) narcissists (Kaufman et al., 2020). Surprisingly, we found that ML models, well-suited for identifying nonlinear or interactive effects, did not provide much insight beyond what linear regression models characterized. One possibility is that—within this dataset at least—there were relatively few nonlinear or interactive relationships with well-being to identify, providing little value to ML above and beyond the value of linear regression models. Alternatively, well-being may hold fewer nonlinear and interactive relationships with other constructs than previously thought.

Most of our results were consistent with previous work on the key predictors of SWB (see Diener et al., 2018; Wienk et al., 2022, for reviews). However, our results highlight some relatively neglected constructs in the SWB literature. The importance of self-esteem and physical health is somewhat greater than previous studies indicate, and most notably, perceiving oneself as in control of one's life—in particular, with regard to one's finances, health, and work—appears to be more strongly associated with SWB than previously thought. Finally, although all measures were completed via self-report, features reflecting subjective evaluations consistently demonstrated stronger associations with SWB than did features reflecting relatively more objective characteristics.

The results of this study provide future SWB researchers with an ordered list of potential predictors of SWB to investigate further—for example, to test as causes of well-being in experimental work (e.g., RCTs; cf. Boiler et al., 2013) or, alternatively, to test as possible consequences of being a happy person (cf. Lyubomirsky, King et al., 2005). Moreover, our findings offer an important insight into the dynamics of well-being: Most variance appears to be linear and non-interactive. However, increasing levels of nonlinearity and interactivity may be identified in future studies when more granular predictors (e.g., traits or facets relative to domains) are considered. In sum, we hope these findings advance understanding of the most likely causes (and consequences) of SWB and shift how well-being scholars interpret, theorize about, design, and analyze their future studies.

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