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Why do low spirits last? Investigating correlates of cumulative unhappiness using German panel data

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Abstract
Experiencing states of unhappiness is normal and part of human existence. Yet, if these states occur often or for longer periods of time, this can become a large burden and greatly reduce a person's overall quality of life. I refer to these states as cumulative unhappiness, and I empirically investigated which factors and variables are correlated with them. Using large-scale German panel data (*N* = 8,646; mean age = 51.7 years, SD = 10.7 years), I attempted to model the correlates of cumulative unhappiness over a period of nine years and included factors such as sociodemographic-background variables, social origin, education, income, household situation, social capital, personality traits, unemployment, and health. Bivariate analyses indicated that health and household income are the two most relevant predictors of unhappiness. In multivariate modeling using dominance analysis, I demonstrated that about 26% of the total variation of cumulative unhappiness can be explained by all independent variables together. In these analyses, the most relevant influential factors were health (14.8%), social status and income (4.0%), and social capital (3.1%). These results indicate that cumulative unhappiness can be explained to some extent.

Keywords Unhappiness · Well-being · Life satisfaction · Dominance analysis · Prediction · Correlation

Introduction

The field of positive psychology studies factors that contribute to a happy human life and explain why and when humans flourish (Kahneman et al., 1999). This research is highly relevant as happiness, which is sometimes also referred to as well-being or life satisfaction, is one of the most relevant goals that humans aspire to. However, the opposite of this positive position, unhappiness, deserves attention as well. While being unhappy cannot be avoided, and all human beings experience negative emotional states from time to time, this can become a serious problem when these episodes are long, resulting in persistent unhappiness (Sapolsky, 2007). Associated factors, such as mental health problems, states of depression, or even suicidal thoughts, are a large burden on the individual but also a challenge for society as a whole (Pincus & Pettit, 2001). To function well, a modern society requires engaged and active citizens that contribute their work and energy to various parts and aspects of society, for example, in the workforce; through relationships with relatives, friends, and other people; while participating in the democratic process; or by being interested in overcoming problems and challenges, such as economic downturns or climate change. Unhappy people, and especially clinically depressed ones, can lose their interest in these aspects and life altogether, which can influence a society negatively if too many individuals are affected by such mental states, not even counting costs for medical treatment (Thomas & Morris, 2003). Obtaining a better understanding of which factors are related to unhappiness and that predict or even cause it can be considered a significant goal in happiness studies, for this is the first step in combatting and reducing individual states of unhappiness.

The present study adds to this research field and takes a longitudinal perspective to understand which influences are associated with being unhappy more often or going through persistent unhappiness. While many studies only have information about a single point in time, longitudinal studies survey respondents regularly to paint a more complete picture of what their lives look like. This approach is highly relevant as it is able to investigate *processes* instead of *states*, easing the understanding of what is happening,

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sometimes even allowing for the deduction of causal inferences. Making robust and validated statements about causality in the social sciences is, however, a major challenge, and overstatements happen regularly when caution would be the wiser choice instead (Hernán, 2018). Given the scope and data available, the present study attempts to answer a more modest research question: What are relevant factors and variables that are correlated with cumulative unhappiness? In this context, *cumulative* refers to being unhappy for longer periods of time or experiencing states of unhappiness more often, even if not continuously. By drawing information from a large German longitudinal dataset, including a rich set of explanatory variables, relevant conclusions can be drawn for the adult population.

State of research

In general, unhappiness has attracted much less research attention than its counterpart (Haybron, 2008). However, it must be made clear from the beginning that research findings on happiness cannot be easily generalized and applied to unhappiness by assuming that the opposite of the conclusion holds true. To give an intuitive justification for this, nonlinear effects are highly relevant, meaning that saturation or ceiling effects can occur, and most trends in the social sciences are not linear by nature. A classic example is income: Giving a fixed amount of money to a poor person will increase happiness much more than giving the same amount to a rich person (Vendrik & Woltjer, 2007). Understanding unhappiness is clearly not the same as understanding happiness and, therefore, deserves a separate focus of attention. From a policy perspective, this can be understood through the following question: What must be done to increase the happiness of a certain group of individuals with average happiness (average in comparison to the entire country) to an above-average level? However, if the question is what must be done to increase the happiness of a group of individuals with below-average happiness to an average level, the answers (and policies) might differ vastly.

Numerous studies have been conducted to investigate correlates, predictors, or causes of unhappiness. The themes that are apparently most relevant are age (Bittmann, 2021; Blanchflower, 2020; Blanchflower & Oswald, 2009), income (Becchetti & Santoro, 2007; Saunders, 1996), income inequality (Becchetti et al., 2014, 2022; Oshio & Urakawa, 2014; Shields & Wailoo, 2002), being unemployed (Clark, 2006; Clark & Oswald, 1994; Gerlach & Stephan, 1996; Longhi et al., 2018; Winkelmann & Winkelmann, 1998), social status (Bhuiyan, 2018; Chen et al., 2021; Haller & Hadler, 2006), degree of urbanization (Okulicz-Kozaryn, 2022; Okulicz-Kozaryn & Mazelis, 2018), mental (Layard et al., 2013) and physical health (Graham et al., 2011), being overweight (Erickson et al., 2000; Sato, 2021), family and social relations (Haller & Hadler, 2006; Webb et al., 2017), marital status (Coombs, 1991), and personality traits (Costa & McCrae, 1980; Hayes & Joseph, 2003; Spangler & Palrecha, 2004).

However, studies that systematically compare various factors and attempt to rank them by their relative importance are much rarer. Often, only regression coefficients are reported with their standard errors, which are not adequate for estimating their relative influence. This is the case as often unstandardized regression coefficients are reported, and measurement and scales of variables can differ greatly. Another obstacle is that these studies often include multiple countries and attempt to test the influence of macro variables that only vary between countries (but not within a country), such as GDP or social inequality. To cite a few examples (where some sort of happiness is the dependent variable), one study using 17 European countries (N > 30,000) reported that the main model explained 22.5% of the total variance (adjusted R^2), and the most influential explanatory variable was the satisfaction with the household income, according to the reported t-statistic (Doherty & Kelly, 2010). Another study with 34 countries (N > 54,000) computed an R^2 value of 26.5%, and according to their standardized regression coefficients, the financial situation and the subjective health were the two single most relevant predictors (Haller & Hadler, 2006). A third study using a huge international dataset from 1975 to 1992 (N > 270,000) was able to explain only about 8% of happiness (Tella et al., 2003). Interestingly, despite using many macro indicators and some individual ones, in this study health was not regarded at all. It is striking that despite the differing samples and also the varying number of explanatory variables, the conclusions were rather similar, just as the explained variances. However, while the total number of cases was high, these analyses looked at cross-sectional data and focused more on country differences than on individual differences, which warrants criticism. Another study with a rather special population (elite athletes) concluded that psychological factors such as self-esteem or stress have the most power to explain various forms of happiness (Denny & Steiner, 2009).

In summary, while some forms of happiness have been of great interest in the past, there are some research gaps. First, regarding the outcome, only happiness has been considered and not the opposite, meaning unhappiness. This might seem like a trivial difference, yet I argue that looking specifically at unhappiness is also relevant because it is not certain that opposite conclusions of previous results always hold true, due to nonlinear and ceiling (or bottom) effects. Second, some studies have focused on a few key aspects yet did not attempt to compare many influences. If they did, they often did not rank these influences properly according to modern statistical approaches and instead relied on rather crude comparisons of regression coefficients or t-statistics. Third, they usually did not take the longitudinal perspective into account, which is a major shortcoming. While being unhappy at some points in time is normal, prolonged or recurring episodes are much more problematic and deserve more research attention. By putting cumulative unhappiness into focus and utilizing appropriate statistical approaches, the following empirical analyses go beyond what has been investigated so far.

Empirical analyses

Data and sample

The following analyses are based on the adult cohort of the National Educational Panel Study (NEPS), known as starting cohort 6 (SC6).[1] The NEPS is one of the most ambitious research projects in Germany for understanding in greater detail the role of education for the entire course of life (NEPS Network, 2022). NEPS SC6 was originally established with a pilot study in 2007/2008 and had its first regular survey wave in 2009/10. Until 2020/21, a total of 12 regular survey waves were conducted because respondents were interviewed annually. The NEPS provides a rich source of relevant information since all major areas of life are included in the survey program, such as (further) education, sociodemographic background, psychological measurements, satisfaction, friends, and even cognitive performance tests. Due to the long-running nature of the panel without recent refreshment samples, the SC6 population has aged continuously and is no longer perfectly representative of the overall German population.

For the following empirical analyses, the sample was slightly restricted to ensure a high internal validity. First, only NEPS surveys 4 to 12 were included (conducted from 2011/12 to 2019/20). The earlier waves were excluded because in wave 4 a major refreshment sample was drawn, meaning that for a large share of the resulting sample, no prior information on many key variables was available (as no retrospective information was gathered on variables like life satisfaction). Also, NEPS wave 13 was excluded, as this survey was conducted after the onset of the COVID-19 pandemic, which must be seen as having been highly impactful for life satisfaction in general. To avoid disturbances due to these very special circumstances, this wave was not included. The second restriction is that only individuals that participated in at least six out of the nine conducted waves were retained in the sample. This restriction was imposed in order to avoid the imputation of information for participants with only little data available, which could create even more bias or variance. Other missing information (item-non-response) was imputed, which is explained in more detail below. The final sample size after enforcing the restrictions was 8,646.

Strategy of analysis

As described, the NEPS provides panel data for a rich set of variables over a long period of time, which is highly beneficial for the intended analyses. Yet it must be made transparent that even this high-quality survey comes with limitations. While making statements about causality can be considered as the holy grail of empirical social research, I believe that it is not feasible to make these statements with the data available and the posed research question. An example can help to explain these limitations: If the research question is intended to estimate the causal impact of marriage on life satisfaction, this can probably be achieved quite well with the NEPS data as the “treatment” (marriage) can be considered a single event in time. After considering anticipation effects, some analyses, such as fixed-effect regression models, are probably able to approximate causality quite well. However, this requires that enough time is observed before and after the event and that no unobserved confounders influence the process. As the presented research question outlines, the goal of the current study is to investigate the influence of many variables and test them against each other. Some are not “events” but long-lasting states, where it is rather unclear when they have even formed. Personality traits, as measured using the Big Five inventory, are a good example. However, not only psychological but also sociological measurements are affected, such as social networks or social status, which develop over long periods of time. Also, participants were rather old at the time of their first survey (older than 25 years in 2011/12), meaning that a long and relevant time of their life has not been observed in detail. A second major problem is that variables were measured at quite different time points in the NEPS study, which means that using them all together in the same analysis and differentiating causal effects is highly problematic. Therefore, all of the following analyses should be viewed more as correlations or predictors and less as causal influences. The findings can still be highly relevant, especially for guiding further studies that focus on the causal impact of a few key variables and processes.

Next, the concrete analytical strategy is outlined. As it is the goal of the study to measure how *cumulative* unhappiness can be explained, the panel nature of the study is of the greatest relevance. It would be ideal to know precisely how long an individual is in a state of unhappiness,

[1] This paper uses data from the National Educational Panel Study (Blossfeld & Roßbach, 2019). The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi, Germany) in cooperation with a nationwide network.

measured in days or weeks. However, this is highly difficult to measure in most quantitative surveys, and only one measurement of overall life satisfaction is available per individual and year in the SC6 data. The method that was chosen for the present study was to count the number of survey waves in which an individual reported below-average life satisfaction, which is considered a state of unhappiness. To do so, the average satisfaction (arithmetic mean) of the sample was computed for each survey wave, along with the standard deviation. Any individual that reported a life satisfaction that was at least one standard deviation below the mean value of the survey wave was counted as being in a state of unhappiness at that point in time. Afterwards, these values were summed for each participant, which provided the total number of waves of reporting below-average life satisfaction. The outcome variable is hence a count variable with values between 0 and 9. To compute how this dependent variable is related to all independent variables, a Poisson regression model was selected (For testing statistical robustness, analyses were repeated using a negative binomial regression model.). For each independent variable, two results were computed: first, the bivariate result, meaning that no other variables were included in the model to report the "raw" effect. Afterwards, one large multivariate model was estimated, meaning that the effect of the independent variables should be seen as "under control" of all other variables in the model. Doing this makes it possible to account for the interrelation of explanatory variables.

Finally, a dominance analysis was conducted. This well-established approach is useful for estimating how much *additional* variance a variable (or set of variables) explains in the dependent variable (Azen & Budescu, 2003; Budescu, 1993). The naive approach of conducting a series of nested regression models and adding explanatory variables in a stepwise fashion is not appropriate as soon as explanatory variables are correlated, which is usually the case. By conducting a large number of regression models where all potential combinations of explanatory variables are tested exhaustively, the additional explanatory power can be quantified. While this approach is computationally intensive, it is well suited to estimating the overall impact a variable has on the outcome.

All analyses were computed in Stata 16.1; the dominance analyses were computed using the package *domin* (Luchman, 2015). To account for item-nonresponse, data were imputed using multiple imputation by chained equations (MICE). Information on the amount of imputed data is provided in Table 1 (see chapter 4). A total of 30 imputed datasets were generated and their quality assessed by established standards (e.g., no generation of impossible values, statistical convergence). For most variables, predictive mean matching was selected as an imputation algorithm. Average marginal effects for the regression models were computed using the package *mimrgns* (Klein, 2014).

Operationalization

As the number of explanatory variables is high, they have been grouped together thematically for a more convenient overview. Note that many variables that are continuous by nature were recoded into categories to account for potential nonlinear effects. Another peculiar aspect is the handling of variables that are potentially time varying. The final analysis is cross-sectional by nature so that all of these variables have to be reduced to one single state. Depending on the scaling of the variable and how often it was measured, distinct solutions have been chosen. If the variable is nominal, such as region of residence, the mode over all survey waves has been selected. Others, which can fluctuate more often, such as income, were accounted for by taking the median over all waves to give the robust average. If some variables were measured only twice with larger gaps, the earlier response was counted to reduce the potential influence of reverse causality.

Based on previous research findings, key areas of interest were selected to explain and predict cumulative unhappiness (the independent variables). The first of these groups are *sociodemographic-background* variables, such as gender, age, or place of residence, and *social origin*, such as income, social status, or education level. As the state of research outlined above has shown, these factors are well-established correlates of unhappiness. While low incomes restrict what a person can buy and access in a society, low levels of social status are also associated with low happiness (Anderson et al., 2012). Education can provide the means to deal with unhappiness and find solutions to overcome problems and obstacles. The third group is *unemployment*, which has been identified as one of the most relevant factors for unhappiness, as not being able to provide for oneself and one's own family is problematic; furthermore, unemployment is associated with a loss of purpose in society. The fourth group is *social capital*, which refers to the extent to which social networks are available to deal mentally and materially with problems and states of unhappiness. The final groups are *personality traits*, which are mostly stable and can be seen as the mental dispositions of a person, and *health measures*, which were one of the strongest predictors in the previously cited references on unhappiness.

Cumulative unhappiness

In each survey wave, respondents were presented with the following: "I would like to begin by asking you a few questions about how satisfied you are with various aspects of your life. Please answer using a scale of 0 to 10. '0' means

Table 1 Descriptive statistics

	Mean	SD	Skew	Kurt	Min	Max	Share imputed
Number of waves with below-average happiness	1.40	2.16	1.79	5.49	0	9	0.068
Female participant	0.51	0.50			0	1	< 0.05
Age in years in 2015							< 0.05
29 to 39	0.16	0.37			0	1	
40 to 50	0.27	0.44			0	1	
51 to 61	0.37	0.48			0	1	
62 to 71	0.20	0.40			0	1	
Migrant	0.16	0.37			0	1	< 0.05
East Germany	0.21	0.41			0	1	< 0.05
Educational level							< 0.05
Low	0.19	0.40			0	1	
Intermediate	0.32	0.47			0	1	
Higher education eligibility	0.19	0.39			0	1	
University of applied sciences	0.10	0.30			0	1	
University	0.20	0.40			0	1	
ISEI							0.165
16 to 25	0.10	0.30			0	1	
25 to 45	0.34	0.47			0	1	
45 to 65	0.33	0.47			0	1	
65 to 90	0.23	0.42			0	1	
ISEI of father							0.154
16 to 25	0.14	0.34			0	1	
25 to 45	0.49	0.50			0	1	
45 to 65	0.16	0.37			0	1	
65 to 90	0.22	0.41			0	1	
Equivalent HH income							0.123
Up to €1,000	0.13	0.34			0	1	
€1,000 to €1,500	0.26	0.44			0	1	
€1,500 to €2,000	0.27	0.45			0	1	
€2,000 to €3,000	0.25	0.43			0	1	
More than €3,000	0.087	0.28			0	1	
Time unemployed in months							< 0.05
0	0.78	0.42			0	1	
Up to 12 months	0.069	0.25			0	1	
12 to 24 months	0.037	0.19			0	1	
24 to 48 months	0.047	0.21			0	1	
More than 48 months	0.070	0.26			0	1	
Marital status							< 0.05
Single	0.15	0.36			0	1	
Married	0.71	0.45			0	1	
Divorced	0.093	0.29			0	1	
Widowed	0.042	0.20			0	1	
Number of people in the HH							< 0.05
1	0.080	0.27			0	1	
2	0.28	0.45			0	1	
3 to 4	0.50	0.50			0	1	
More than 5	0.14	0.35			0	1	
Number of children in the HH							0.104
0	0.66	0.47			0	1	
1 to 2	0.29	0.46			0	1	

Table 1 (continued)

	Mean	SD	Skew	Kurt	Min	Max	Share imputed
3 or more	0.043	0.20			0	1	
Social capital	0.031	0.98	-0.47	2.69	-2.71	1.74	< 0.05
Extraversion	3.38	0.93	-0.061	2.42	1	5	< 0.05
Agreeableness	3.58	0.60	-0.12	3.14	1	5	< 0.05
Conscientiousness	4.05	0.72	-0.38	2.58	1	5	< 0.05
Neuroticism	2.58	0.82	0.21	3.06	1	5	< 0.05
Openness	3.50	0.92	-0.15	2.37	1	5	< 0.05
Self-rated health	3.74	0.70	-0.49	3.71	1	5	< 0.05
Physical health score	51.8	9.30	-0.87	3.53	12.9	73.8	0.316
Mental health score	50.1	10.4	-0.68	3.32	6.88	78.5	0.316
Self-worth	43.1	4.88	-0.99	4.31	16	50	0.052
Drinking alcohol							< 0.05
Never	0.098	0.30			0	1	
Once per month	0.21	0.41			0	1	
2–4 × per month	0.31	0.46			0	1	
2–3 × per week	0.25	0.43			0	1	
More than 4 × per week	0.13	0.34			0	1	
BMI classification							< 0.05
Normal or underweight	0.41	0.49			0	1	
Overweight	0.39	0.49			0	1	
Obesity I	0.14	0.35			0	1	
Obesity II/III	0.053	0.22			0	1	
Observations			8646				

Source: NEPS SC6, imputed data (M = 30). *HH* household

that you are totally and utterly dissatisfied; '10' means that you are entirely satisfied. […] How satisfied are you currently with your life in general?" For the analysis of the given research question and overall life satisfaction, the NEPS recommends using this single variable and not generating a compound score, even if sub-dimensions of happiness were also measured. This scale has 11 distinct levels in total. As was already described above, the average happiness and standard deviation was computed for each survey wave. If a respondent reported a response that was at least one standard deviation below the wave-mean, she was counted as being unhappy in that wave. The total number of times a respondent was recorded at below-average happiness was used to measure his or her cumulative unhappiness. It should also be highlighted that cumulative unhappiness, as used in this study, is not the same as *average* unhappiness, which could be operationalized as averaging the values over all waves. By looking at each wave separately and comparing each value to the mean-value, more information can be extracted out of the data.

Sociodemographic background variables

The gender of the respondents was measured as binary, either male or female. The age was computed in 2015 (wave 8) and grouped as follows: 29 to 39 years, 40 to 50 years, 51 to 61 years, 62 to 71 years. This also shows that all respondents were between 29 and 71 years old at that point in time. If the person was born abroad, or at least one of their parents was born abroad, this was counted as having a migration background, otherwise not. If the person lived predominantly in East Germany, this was counted as living in the East, otherwise not.

Social origin

The precise measurement of social origin is of the greatest interest as this construct can involve aspects such as education, the financial situation of the household, or the social status in society. First, the highest educational qualification was measured with five levels on the CASMIN scale: no degree or lower degree (*Hauptschulabschluss*) / intermediate degree (*Realschulabschluss*) / higher education eligibility (*Abitur*) / university of applied science degree (UAS, *Fachhochschulabschluss*) / any university degree. Second, the total post-tax monthly household income was taken and the median formed over all available survey waves. Then, the equivalent household income was computed by accounting for the number of other adults and children living in the same household. The categories are €0 to €1,000 / €1,001 to €1,500 / €1,501 to €2,000 / €2,001 to €3,000 / more than €3,001. Third, the social status was measured using the International Socio-Economic Index of Occupational Status (ISEI), which is based on the occupation held. Since occupations can change over time, the NEPS provides retrospective information for all jobs. I considered the time between 2008 and 2018 and generated the average ISEI for all occupations held in this time span, weighted by the duration of a specific occupation. If no occupation or ISEI was available for this time (which can be possible for partners who stay at home), the ISEI of the working partner was used, if available. If no information could be found, the data was imputed. The ISEI, which can go from 16 to 90, is also categorized as follows: 16 to 25 / 25 to 45 / 45 to 65 / 65 to 90.[2] Fourth and finally, the highest ISEI of the father was also included, which was measured with the same categories. When taken together, these variables give a good impression of various sub-dimensions of social origin.

Unemployment

The cumulative time unemployed was measured between 2008 and 2018. To do so, all reported episodes of unemployment within this time span were added together. If the unemployment episode started and ended within the same month, 15 days were assumed since no daily information was available. The resulting variable was grouped into the following categories, measured in months: 0 / 1 to 12 months / 12 to 24 months / 24 to 48 months / more than 48 months.

Social capital

The social capital of an individual was measured with multiple variables. First, the marital status was taken from wave 4 of the NEPS (2011/12): being single / being married or in a civil union / being divorced / being widowed. Clearly, this measurement is not precise as marital status can change over time, yet it is not feasible to account for all variations in a cross-sectional analysis. An early point in the survey (wave 4) was chosen to reduce the problem of reverse causality. Second, the total number of individuals in the household was measured as the maximum number of individuals ever living in the household over the time surveyed. The categories are 1 / 2 / 3 to 4 / 5 or more. Third, the number of children was measured as the maximum number of children below 18 ever living in the household with the following categories: 0 / 1 to 2 / 3 or more. Fourth, the social capital was measured with the "position generator" (Schulz et al., 2017). This instrument measures whether the respondent knows at least one person with a specific occupation, for example, a lawyer, a teacher, a translator, and so on. The more individuals with specific occupations the respondent knows, the higher his or her social capital. As each occupation can be associated with an ISEI value, the average total social capital can be measured that way. This variable is mean-centered and standardized (z-standardization). Higher values indicate an overall higher social capital.

Personality measurements

The established Big Five inventory was surveyed in wave 5 of the NEPS (2012/13) and contains the dimensions extraversion, agreeableness, conscientiousness, neuroticism, and openness. The constructs were measured using the German 10-item short version (Rammstedt & John, 2007) in wave 5 of the survey.

Health measurements

First, self-rated health was measured in each wave of the NEPS. To take the average health, the median over all available survey waves was formed. The wording is as follows: "I now have a brief question about your health. How would you generally describe your state of health?" The responses were measured with five levels from 1 (very poor) to 5 (very good). This item is useful in order to have information on subjectively perceived health. Second, for a more objective measurement, physical and mental health were measured using the 12-item Short Form Survey, which uses 12 items to record overall physical and mental health by asking questions such as, "During the past week, have you had any of the following problems with your work or other regular daily activities as a result of your physical health?" (Andersen et al., 2007). These items were surveyed in wave 4. Third, personal self-worth was measured following the conceptualization of Rosenberg in wave 6 (2013/14) (von Collani & Herzberg, 2003). It ranges from 14 to 50, where higher values stand for higher self-worth. Fifth, the body mass index (BMI) was measured by taking the median weight and height over all available survey waves. The result was classified according to the WHO standard from 2008 as follows: Up to 25 (Normal weight or underweight[3]) / 25 to 30 (Overweight) / 30 to 35 (Obesity I) / more than 35 (Obesity II/III). Sixth and finally, how often the respondent consumed alcohol was measured ("How often do you consume alcoholic

[2] Note that for any continuous measurement (where information on the decimal places is available; e.g., income, in contrast to age in years), the cuts are up to and including the limit. Hence, for the ISEI, "up to 25" means up to 25, including this limit. Any number greater than 25 is in the next category, and so on. This has been shortened in the following tables for a more compact presentation.

[3] Since being underweight (BMI < 18.5) is very rare in the sample, no extra classification has been coded.

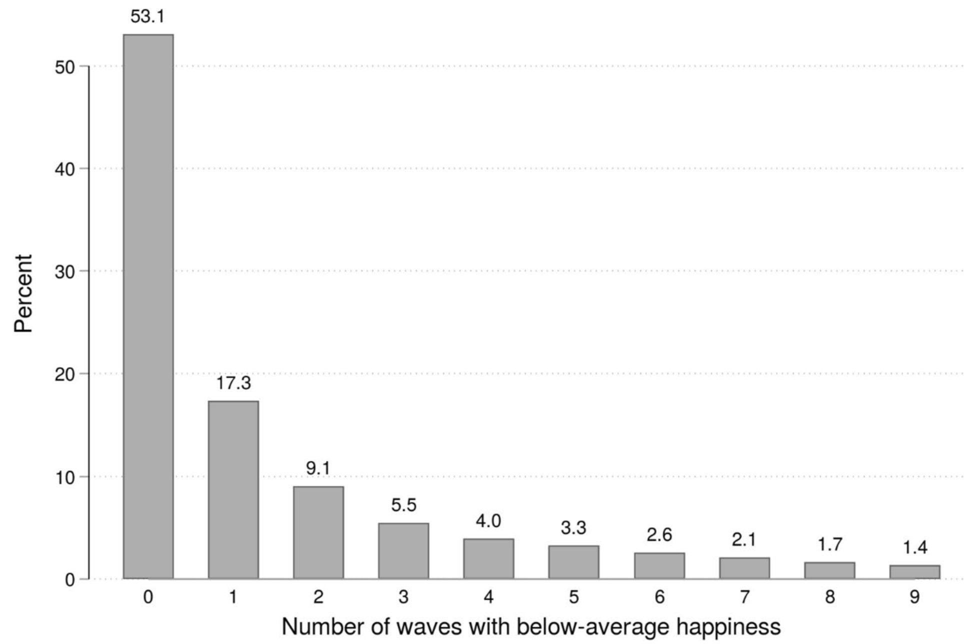

Fig. 1 Total number of waves with below-average happiness per respondent. Source: NEPS SC6, imputed data (M = 30). Higher numbers indicate a larger cumulative unhappiness

drinks, e.g., a glass of wine, beer, a mixed drink, spirits or liqueur?"); this was measured in wave 4 (or wave 7, if no information was available from wave 4) with the following scale: never / once per month / 2–4 × per month / 2–3 × per week / more than 4 × per week.

Results

Descriptive findings

The overall average satisfaction was highly stable and always between 7.5 and 7.7 (with standard deviations between 1.4 and 1.6) for all survey waves. This means that aggregated satisfaction is rather constant over time, which of course does not mean that no individual satisfaction is constant as well. The total number of survey waves with below-average satisfaction is visualized in Fig. 1.

As it turns out, the majority (about 53%) of all respondents never reported any survey with below-average values, yet a large minority of about 47% did. Slightly more than 11% of all respondents reported below-average happiness for at least five survey waves, which is more than half of the entire survey time of up to nine waves. Descriptive results for all variables are reported in Table 1.

Regression analysis

In this section, the results of the Poisson regression models are reported. First, bivariate associations are reported, followed by the multivariate results (see Table 2). For a more convenient interpretation, average marginal effects (AMEs) are reported. As an example, consideration can be given to the effect of gender (Since reverse causality can be excluded for this variable, referring to an *effect* is probably adequate). The AME for women is 0.231 and statistically highly significant in the bivariate model. This means that women report, on average, 0.23 more waves with below-average happiness than men and are, apparently, unhappy more often since the value is larger than zero. However, this association between gender and unhappiness vanishes as soon as other variables are considered in the same model, as the computed AME changes to -0.048 in the multivariate model. This result is no longer statistically significant, and even the sign changes. This means that as soon as all other variables are considered, gender is no longer associated with unhappiness, and this association from the bivariate model is, therefore, spurious. While the bivariate results can be relevant for prediction or for samples where little information is known or only few explanatory variables are available, the multivariate results are better able to understand what is actually relevant. Some variables are associated with a higher number of reported surveys with below-average happiness, such as being older or drinking more alcohol. For others, this association is negative, such as for having a higher education, earning more money, or reporting better health. These people reported being unhappy less often, on average.

Dominance analysis

While a regression analysis is helpful to understand how variables are related to the outcome (positively or negatively) and if these associations are statistically significant, they are hardly able to determine the relative importance

Table 2 Average marginal effects for bi- and multivariate associations with cumulative unhappiness

	Bivariate			Multivariate		
	AME	SE	Explained var. (%)	AME	SE	Explained var. (%)
Female	0.231***	(0.03)	0.23	−0.048	(0.03)	0.56
Age in years in 2015			0.58			
29 to 39	Ref			Ref		
40 to 50	0.254***	(0.04)		0.310***	(0.04)	
51 to 61	0.453***	(0.04)		0.388***	(0.05)	
62 to 71	0.534***	(0.04)		0.326***	(0.05)	
Migrant	0.043	(0.04)	0.00	−0.069	(0.04)	
East Germany	0.302***	(0.03)	0.25	0.066	(0.03)	
Education level			2.89			3.97
Low	Ref			Ref		
Intermediate	−0.436***	(0.04)		−0.054	(0.04)	
Higher education eligibility	−0.805***	(0.05)		−0.147**	(0.05)	
University of applied sciences	−1.059***	(0.05)		−0.197**	(0.06)	
University	−1.148***	(0.04)		−0.155**	(0.06)	
ISEI			3.39			
16 to 25	Ref			Ref		
25 to 45	−0.576***	(0.08)		0.023	(0.06)	
45 to 65	−1.045***	(0.07)		0.021	(0.06)	
65 to 90	−1.460***	(0.07)		−0.104	(0.07)	
ISEI of father			0.71			
16 to 25	Ref			Ref		
25 to 45	−0.059	(0.05)		0.039	(0.04)	
45 to 65	−0.381***	(0.06)		−0.053	(0.06)	
65 to 90	−0.498***	(0.05)		0.043	(0.06)	
Equivalent HH income			7.01			
Up to €1,000	Ref			Ref		
€1,000 to €1,500	−1.127***	(0.07)		−0.205***	(0.05)	
€1,500 to €2,000	−1.646***	(0.07)		−0.479***	(0.06)	
€2,000 to €3,000	−2.006***	(0.06)		−0.714***	(0.06)	
More than €3,000	−2.245***	(0.07)		−0.903***	(0.08)	
Time unemployed in months			2.94			1.10
Never	Ref			Ref		
1 to 12	0.317***	(0.05)		0.396***	(0.06)	
12 to 24	0.652***	(0.08)		0.259***	(0.07)	
24 to 48	0.544***	(0.07)		0.179**	(0.06)	
More than 48	1.739***	(0.07)		0.251***	(0.05)	
Marital status			3.86			3.13
Single	Ref			Ref		
Married	−0.998***	(0.04)		−0.510***	(0.05)	
Divorced	0.112	(0.07)		0.056	(0.06)	
Widowed	0.343***	(0.09)		0.080	(0.08)	

Table 2 (continued)

	Bivariate			Multivariate		
	AME	SE	Explained var. (%)	AME	SE	Explained var. (%)
Number of adults in the HH			1.94			
1	Ref			Ref		
2	−0.930***	(0.07)		−0.113*	(0.05)	
3 to 4	−1.279***	(0.06)		−0.239***	(0.06)	
More than 5	−1.347***	(0.07)		−0.382***	(0.07)	
Number of children in the HH			0.88			
0	Ref			Ref		
1 to 2	−0.434***	(0.03)		0.015	(0.04)	
3 or more	−0.633***	(0.05)		0.095	(0.10)	
Social capital	−0.332***	(0.01)	1.96	−0.047**	(0.01)	
Extraversion	−0.290***	(0.02)	1.27	−0.026	(0.02)	2.21
Agreeableness	−0.146***	(0.02)	0.13	−0.135***	(0.02)	
Conscientiousness	−0.088***	(0.02)	0.07	0.049*	(0.02)	
Neuroticism	0.593***	(0.02)	4.25	0.085***	(0.02)	
Openness	−0.067***	(0.02)	0.07	0.063***	(0.02)	
Self−rated health	−1.164***	(0.02)	14.46	−0.704***	(0.03)	14.81
Physical health score	−0.051***	(0.00)	4.73	0.000	(0.00)	
Mental health score	−0.062***	(0.00)	8.80	−0.029***	(0.00)	
Self−worth	−0.132***	(0.00)	9.95	−0.051***	(0.00)	
Drinking alcohol			1.58			
Never	Ref			Ref		
Once per month	−0.377***	(0.06)		0.049	(0.05)	
2–4 × per month	−0.896***	(0.06)		−0.061	(0.05)	
2–3 × per week	−0.946***	(0.06)		−0.036	(0.05)	
More than 4 × per week	−0.701***	(0.06)		0.204***	(0.06)	
BMI classification			0.84			
Normal or underweight	Ref			Ref		
Overweight	0.049	(0.03)		−0.054	(0.03)	
Obesity I	0.437***	(0.04)		−0.017	(0.04)	
Obesity II/III	0.899***	(0.07)		−0.089	(0.06)	
Total Pseudo R^2			–			25.84
Observations	8646			8646		

Source: NEPS SC6, imputed data (M = 30). Standard errors in parentheses. *HH* household. Explained variance in the dominance analysis refers to the multivariate model

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

for prediction and explanation. Even if some variables are statistically highly significant, this does not automatically mean that much of the overall variance in the outcome can be explained. This is further complicated due to the fact that explanatory variables are often measured on vastly different scales and are usually correlated with each other. For example, in the results presented above, both the household income and the number of adults in the household have statistically significant relationships with the outcome, yet it is not feasible to state which of the two has more influence based on the AMEs alone. Answering such a question is, however, highly relevant in order to understand which factors are most strongly associated with unhappiness, which can be useful to guide further research or even design interventions. To solve this problem, dominance analysis can be used as it quantifies the additional explanatory power of a variable or a set of variables under control of all other variables in the model. Since the number of independent variables is rather large, it is not feasible to compute this additional part for each one, since the number of required regression models grows exponentially and is, hence, computationally not viable. To overcome this obstacle, explanatory variables are included as thematically grouped sets. Results are presented in Table 2. As the regressions are Poisson models, pseudo-R^2 values are reported.

All explanatory variables together explain almost 26% of the overall variance of the dependent variable. Given that human life is highly complex and contingent, this can be regarded as a rather satisfactory result, which is also close to what previous studies have been reporting. When this total variance is decomposed, it becomes clear that health factors are, by far, the most relevant influence with a share of almost 15%. In second place are social status factors, which account for about 4%. Social capital factors come in third with about 3%, and personality traits are fourth, with about 2%. What is obvious from this analysis is that health factors are, with a large margin, the most relevant factors correlated with cumulative unhappiness. Since the results outline that health factors are, by far, the most relevant correlate of unhappiness, these variables have been decomposed in an additional analysis to see how their share (14.81%) is divided. It turns out that self-rated health has the biggest impact (4.4%), followed by the mental health score (3.3%) and self-worth (2.6%). The influence of the other factors is below 1% each. It's important to note that this extra computation is also under control of all other variables as included before, yet the total share of all health variables does not add up to 14.81 as the two analyses are not directly comparable. However, it is still useful to gauge approximately which health variable is the most relevant.

Discussion

As the results outline, there are some factors that are rather strongly related to cumulative unhappiness. Of greatest relevance is the concept of statistical control that has been applied in the multivariate analyses, as this makes it possible to come to the "core" of the associations and avoid incorrect conclusions due to spurious correlations. By comparing bi- and multivariate coefficients, it is obvious that some factors that initially show significant correlations completely lose them as soon as other variables are also included. This is crucial for approximating causal influences. While this has not been done in the present analyses, it can be helpful for future studies that focus on distinct aspects or key variables. When discussing correlates, especially health factors must be highlighted, which explain the most variation in the outcome. This is in line with previous research findings that come to the same conclusion. However, for the first time, various influences have been ranked systematically. The findings underline that health is, with a wide margin, the single most important influence, as the health variables taken together explain more than three times the variance that all influences of social status, including the financial situation of the household, do. While these results are to be seen as more correlational than causal, the current analyses do not allow for seeing them as a causal factor. The question remains whether this is a causal explanation or whether reverse causality might be present, meaning that individuals with lower happiness *become* unhealthier. In any case, as the results underline, the nexus of unhappiness and health deserves further attention to disentangle potential causal mechanisms. This is a potential next step for further research projects. By having correlates of unhappiness ranked by their relative importance, the present study helps researchers to pick some areas that deserve special attention in order to explain the genesis of cumulative unhappiness.

To conclude the discussion, the limitations of the analyses must be made transparent. First, only a single country, Germany, is available, which restricts the external validity of the findings. While I believe that the conclusions likely also hold true for comparable (western and industrialized) countries, they might be different for other cultures with a different standard of living. This restriction also means that no macro indicators could be examined. It should also be made transparent that due to the nature of the used panel data, the data available are not perfectly representative of the overall German (adult) population due to panel effects, such as selective dropout over time. Second, as only about one fourth of the total variance of cumulative unhappiness can be explained, the majority of the influences remain underexposed. However, as previous studies also reported similar values, this means that either happiness is a rather volatile or difficult-to-explain construct or that main explanatory factors were not yet identified. Third, many constructs used in the study are subject to measurement error. Clearly, measuring "happiness" or "unhappiness" is a difficult task, and experts might not agree on which items or scales are ideal. The measurement in the NEPS uses a rather widespread approach also used in other large surveys, such as the World Values Survey or the European Social Survey. Especially when subjective variables are measured, measurement error is likely always present and might add some bias to all results, which is, of course, to some extent, unavoidable. Items and scales have been presented and references given for any reader that is interested in reviewing the validity and reliability of the results.

Conclusion

Identifying which factors are correlated with unhappiness is a first step in the process of understanding causal influences. However, instead of a current state of unhappiness, longer lasting episodes or reporting being unhappy more often over time were studied to gain robustness and look for processes that are temporally stable. By using an established German panel study, a large number of potential influences were identified and ranked by their relative importance. It is clear that health is, by far, the single most relevant predictor of cumulative unhappiness, followed by social status and social capital. Overall, the findings are in line with previous findings, yet they present more qualitative data to estimate the strength of associations in more detail. Based on these findings, further research projects might want to establish causal mechanisms and relationships with unhappiness.

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Declarations

Informed consent and ethical approval The authors declare that they have followed the protocols of their work center on the publication of patient and participant data and that all the patients/participants included in the study have received sufficient information and have given their informed consent in writing to participate in that study. The guidelines of the declaration of Helsinki are upheld and respected.

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