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Correlates of Quality of Life, Happiness and Life Satisfaction among European Adults Older than 50 years: A Machine-Learning Approach

Abstract

Background and Objectives: Previous research has documented the role of different categories of psychosocial factors (i.e., sociodemographic factors, personality, subjective life circumstances, activity, physical health, and childhood circumstances) in predicting subjective well-being and quality of life among older adults. No previous study has simultaneously modeled a large number of these psychosocial factors using a well-powered sample and machine learning algorithms to predict quality of life, happiness, and life satisfaction among older adults. The aim of this paper was to investigate the correlates of quality of life, happiness, and life satisfaction among European adults older than 50 years using machine learning techniques.

Research Design and Methods: Data drawn from the Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 7 were used. Participants were 62,500 persons aged 50 years and over living in 26 Continental EU Member States, Switzerland, and Israel. Multiple machine learning regression approaches were used.

Results: The algorithms captured 53%, 33%, and 18% of the variance of quality of life, life satisfaction, and happiness, respectively. The most important categories of correlates of quality of life and life satisfaction were physical health and subjective life circumstances. Sociodemographic factors (mostly country of residence) and psychological variables were the most important categories of correlates of happiness.

Discussion and Implications: This study highlights subjective poverty, self-perceived health, country of residence, subjective survival probability, and personality factors (especially neuroticism) as important correlates of quality of life, happiness, and life satisfaction. These findings provide evidence-based recommendations for practice and/or policy implications.

Keywords: well-being; machine learning; random forest; gradient boosting

1. Introduction

The increase in the proportion of the older population as well as in life expectancy has led to a growing interest in research on subjective well-being (e.g., happiness and life satisfaction) and quality of life. Findings from systematic reviews of successful aging models and concepts revealed that quality of life, happiness, and life satisfaction are key ingredients of successful aging (Fatemeh et al., 2020; Martinson & Berridge, 2014; Young et al., 2009). The aging process is associated with declines in cognitive abilities and physical functioning; notwithstanding, subjective well-being can have positive implications for older people given that negative psychological states may worsen physical and cognitive decline (Corcoran et al., 2013; Steptoe et al., 2015). In addition, subjective well-being and quality of life predict survival and longevity (e.g., Brown et al., 2015). For these reasons, research on subjective well-being and quality of life is an important emerging theme among older adults (Steptoe, 2019b).

Past research on the determinants of subjective well-being has focused on demographic factors, temperament/personality, life circumstances, and intentional activity (Diener et al., 1999; Martin, 2005; Sheldon & Lyubomirsky, 2007). For instance, the importance of Big Five neuroticism, extraversion, and conscientiousness was highlighted by meta-analytic findings (e.g., Anglim et al., 2020). The adverse childhood experiences framework provides reasons to expect that childhood adversities (e.g., physical, sexual and verbal abuse) and other experiences can strongly influence well-being in later life (e.g., Hughes et al., 2016). According to activity theory (Havighurst, 1961; Lemon et al., 1972), older adults are more likely to experience higher quality of life and subjective well-being when they remain active, i.e., when they engage in social and productive activities. There is evidence supporting the relationship between social participation and well-being in later life (e.g., Adams et al., 2011; Huxhold et al., 2014; Mackenzie & Abdulrazaq, 2021). In addition, physical health has been associated with subjective well-being (Diener et al., 1999; Steptoe, 2019a). However, no large study has simultaneously modeled these psychosocial factors to investigate their relative associations to subjective well-being and quality of life among older adults.

2. Purpose of the Present Study

Population ageing in Europe will intensify over the course of the three decades (Grundy & Murphy, 2017). The present research aims to address gaps in the literature and contribute to gerontology and positive psychology fields with an investigation of the psychosocial correlates of subjective well-being and quality of life among a well-powered sample of European adults who are 50 years and older using a machine-learning approach. By taking inductive approaches to data analysis for theory refinement, theory building, and exploration, machine learning approaches focus on detecting patterns from big data and, for these reasons, have demonstrated to be a powerful tool for research in aging (e.g., Chen, 2021; do Nascimento et al., 2022; Lee et al., 2020; Qin et al., 2020). In the present study, most of the factors proposed in the conceptual model proposed by Börsch-Supan (2020a) were included. Specifically, this study contributes to the literature by investigating the association of six categories of psychosocial factors (i.e., sociodemographic factors, personality, subjective life circumstances, activity, physical health, and childhood circumstances) with subjective well-being and quality of life among European adults who are 50 years and older.

3. Method

3.1 Sample and Procedure

This research uses data from the Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 7 (Bergmann, Scherpenzeel, et al., 2019; Börsch-Supan, 2020b; Börsch-Supan et al., 2013). The SHARE survey design was designed to be able to draw inferences about the population of people who are 50 years and older by using probability-based sampling. In SHARE Wave 7, a full coverage of all continental EU Member States, in addition to Switzerland and Israel was achieved. The data collection of SHARE Wave 7 started in March 2017 and lasted until October 2017. Data were collected through in-depth interviews (the vast majority conducted face-to-face) and resulted in 62,500 participants aged 50 years and over (age range 50-105) providing informed consent and completing the interview. A total of 107 potential correlates were included in the present study. Further information on SHARE Wave 7 methodology and participation (e.g., sampling and response rates in SHARE on household and individual level by country) can be found in SHARE Working Paper Series (Bergmann, Kneip, et al., 2019; Bergmann, Scherpenzeel, et al., 2019).

The SHARE study was reviewed and approved by the Ethics Council of the Max Planck Society. In addition, the implementation of SHARE in the participating countries was reviewed and approved by the respective institutional review boards or ethics committees whenever this was required.

3.2 Measures

Outcome Variables. The following question was used to assess happiness: “How often, on balance, do you look back on your life with a sense of happiness?” Responses were provided using a four-point scale ranging from 1 (*Often*) to 4 (*Never*). Scores in this measure were reversed so that higher scores represent greater happiness. Life satisfaction was measured using the following question: “On a scale from 0 to 10 where 0 means completely dissatisfied and 10 means completely satisfied, how satisfied are you with your life?” Single item measures of subjective well-being are widely used in the literature (Cooper et al., 2011) and perform very similarly compared to the multiple-item (e.g., Abdel-Khalek, 2006; Cheung & Lucas, 2014; Jovanović & Lazić, 2020). To measure quality of life among older adults, the CASP-12 (Hyde et al., 2003; Kerry, 2018) was chosen. The CASP-12 is a short version (12-item) of the original CASP-19 scale (Hyde et al., 2003). Participants indicated how often each of 12 specific statements applies to them, using a 4-point Likert scale ranging from 1 (*Often*) to 4 (*Never*). Items examples are: “My age prevents me from doing the things I would like to” and “I feel that life is full of opportunities.” Positive items were reversed, and all items were summed (range 12–48) with higher scores indicating better quality of life. Cronbach’s alpha was good ($\alpha = .83$).

Sociodemographic Variables. Sociodemographic variables included sex, age, education (years of education as well as ISCED 1997 coding of education), marital status, current job situation, country of residence, household type, having a partner, having children, number of children, ever done paid work, ever been married, ever had an unmarried partner, how often married, amount spent on food at home, amount spent on food outside home, and total household income (adjusted for purchasing power parity). Exchange rates that adjust for purchasing power parity were used for non-Euro countries.

Physical Health. Physical health encompassed measures of self-perceived health (with a single item using the answer categories of the SF-36 questionnaire, ranging between “excellent” and “poor”), maximum handgrip strength (with the aid of a dynamometer), orientation in time, limitation with activities (Global Activity Limitation Index), mobility limitations, limitations in activities because of health, number of limitations with activities of daily living (Activities of Daily Living Index), number of limitations with instrumental activities of everyday life, any long-term illness, number of chronic diseases, body mass index, weight, height, number of doctor visits, number of hospital visits, number of hospital overnight stays, having one or more frailty symptoms (falling down, fear of falling down, dizziness, faints or blackouts, and fatigue), and being ever diagnosed/currently having medical conditions (i.e., heart problems, high blood pressure or hypertension, high blood cholesterol, stroke or cerebral vascular disease, diabetes or high blood sugar, chronic lung disease, cancer or malignant tumor, stomach or duodenal ulcer, Parkinson disease, cataracts, hip fracture, other fractures, Alzheimer’s disease, dementia, organic brain syndrome, senility or any other serious memory impairment, other affective or emotional disorders, including anxiety, nervous or psychiatric problems, rheumatoid arthritis, osteoarthritis, or other rheumatism, chronic kidney disease, other conditions, or none). Subjective life expectancy was measured by asking respondents to state their subjective survival probabilities on a scale from 0 to 100 as follows: What are the chances that you will live to be age [T] or more? The target age, T, included in this question was chosen conditional on the participant’s age such that the distance between the current age and the target age varied between 9 and 25 years (SHARE, 2020). For instance, participants aged between 50 and 55 at the time of the interview were presented with a target age of 75 years, while respondents older than 90 years got shorter time horizons with a minimum of six years.

Psychological Variables. A 10-item short version of the Big Five Inventory (Rammstedt & John, 2007) was used to measure the following five important personality traits (known as the Big Five): openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. As a measure of cognitive functioning, recall ability is assessed by reading a list of ten items where the participant is asked which one she or he recalls within one minute. The cognitive functioning indicator is the sum of all words recalled within a minute. The test was repeated twice and a summary score of cognitive functioning was constructed that ranges between 0 and 20 and consists of the sum of the points assigned in both trials.

Activity. Participants were asked to report if they have done and with what frequency any of the following activities in the last twelve months: voluntary or charity work; attending educational or training course; participation in a sport, social, or other kind of club; reading books, magazines, or newspapers; wording or numbering games such as crossword puzzles or Sudoku; playing cards or games such as chess; and taking part in a political or community-related organization. A score of 0 or 1 was assigned to each “no” or “yes” response, respectively. Participation in each of the seven activities as well as the frequency were entered in the analysis as separate variables. In addition, a total score for general level of activity was computed by summing the responses. Also, another total score for the frequency of activity was computed by summing the responses.

Childhood Circumstances. Participants were asked questions about their childhood conditions: childhood health status, any physical injury to disability, number periods of ill health, relationship with parents, physical abuse in childhood, importance of religion at home when growing up, loneliness in childhood, and group of friends in childhood.

Subjective Life Circumstances. Participants reported information about their general life such as perceived income adequacy or subjective poverty (household able to make ends meet) and periods of stress, financial hardship, and hunger. Furthermore, respondents reported if they have ever been the victim of persecution or discrimination.

Interviewer Observations. To control for the potential effect of the circumstances surrounding the interview, information of background interview characteristics reported by the interviewer was included in the analysis: third persons present during the interview, willingness to answer, respondent asked for clarifications, respondent understood questions, and help needed to read showcards.

3.3 Analytic Approach

Analyses were conducted using JASP Version 14.1 (JASP Team, 2020) and the R-package gbm and randomForest. Distributional properties of the dependent variables were appropriate as indicated by absolute values of skewness and kurtosis > 2 (Lei & Lomax, 2005; West et al., 1995). In the analyses, the predictors were treated as categorical, ordinal, or continuous variables as appropriate. Missing data were imputed using both hot-deck or the fully conditional specification imputation procedures (Bergmann, Scherpenzeel, et al., 2019; SHARE, 2020). Two different machine learning algorithms were fine-tuned to achieve the best model prediction of quality of life and subjective well-being: Friedman's gradient boosting machines (GBM) algorithm and Breiman's random forest algorithm. These two machine learning algorithms were chosen because they were the only algorithms[1] that are able to (1) provide data on variable importance and (2) handle categorical and ordinal input variables in addition to continuous variables. For both models, the prediction error on a validation data set was optimized with respect to the number of trees, setting to 100 the maximum number of possible decision trees to be

[1] Among those provided by JASP

considered. Sensitivity tests were carried out to investigate the efficacy of the selection of the hyperparameters. Specifically, concerning the GBM algorithm, 100 to 5,000 number of trees to fit with shrinkage rates between 0.01 and 0.001 were tested. A shrinkage rate below 0.01 with more than 100 trees did not give a significantly improved predictive performance. Therefore, to reduce the computational costs, a shrinkage rate of 0.01 was chosen. Concerning the Breiman's random forest algorithm, the optimal number of trees to grow in each iteration was determined in preliminary tests. These tests revealed that a threshold beyond which there is no significant performance gain was 100 trees.

To provide numerical stability and improve the clustering output, the continuous variables were standardized using the Z-score standardization of a mean of 0 and a standard deviation of 1. The performance of each model was evaluated with the coefficient of determination (R^2) and the root-mean-square error (RMSE) Data were randomly partitioned to 60% train, 20% validation and 20% test. The best model from each approach (i.e., the one with the lower root-mean-square error and, in case of a tie, the highest R^2) was selected. Subsequent analyses were conducted to further disentangle significant effects and determine their effect size using both correlation and ANOVA.

4. Results

Table 1 shows the results of the models predicting quality of life, life satisfaction, and happiness on the training and the test dataset. The results on the test set were similar to the training set. This may indicate that the findings are robust. The gradient boosting algorithm predicting quality of life had the highest R^2, while the other metrics were similar to the random forest algorithm. The gradient boosting algorithm predicting both life satisfaction and happiness had a lower RMSE than the random forest algorithm. Therefore, the findings of the gradient boosting algorithm were selected. The list of variables with a relative influence higher than 0 resulting from the gradient boosting algorithm is shown in Supplementary Table S1. The models were re-evaluated by employing the identified variables with a relative influence higher than 0.

The results are reported in Table 2. There were minor differences between the models employing all the variables and those including the variables with a relative influence higher than 0.

Table 1

Comparison of Machine Learning Algorithms Predicting Quality of Life, Life Satisfaction, and Happiness

		Validation MSE	Test MSE	RMSE	R^2
Quality of life	Random forest	0.468	0.487	0.698	.534
	Gradient boosting	0.484	0.487	0.698	.535
Life satisfaction	Random forest	0.689	0.694	0.833	.325
	Gradient boosting	0.710	0.672	0.820	.334
Happiness	Random forest	0.834	0.808	0.899	.191
	Gradient boosting	0.811	0.806	0.898	.182

Note. MSE = mean squared error; RMSE = root-mean-square error. The prediction results reported are not the averages of many simulations.

Table 2

Re-Evaluation of the Gradient Boosting Algorithm by Employing the Variables with a Relative Influence Higher than 0

	Validation MSE	Test MSE	RMSE	R^2
Quality of life	0.469	0.462	0.680	.551
Life satisfaction	0.683	0.679	0.824	.320
Happiness	0.820	0.827	0.909	.175

Note. MSE = mean squared error; RMSE = root-mean-square error.

4.1 Correlates of Quality of Life

Table 3 presents the order of the ten most important variables resulting from the gradient boosting algorithm for quality of life (the list of variables with a relative influence higher than 0 is shown in Supplementary Table S1). In decreasing order of importance, the first ten variables associated with quality of life were subjective poverty (r_s = -.46), self-perceived (good) health (r_s = .46), mobility limitations (r_s = -.43), neuroticism (r_s = -.37), subjective survival probability (r_s = .36), country (ω = .14), being not bothered by frailty (ω = .14), conscientiousness (r_s = .24), frequency of activities (r_s = .38), and limitations with instrumental activities of daily living (r_s = -.35). To explore differences by country, Supplementary Figure S1 displays mean scores for each country. Southern/Mediterranean and Eastern European countries reported lower scores compared to Central and Northern European countries.

4.2 Correlates of Life Satisfaction

The order of the ten most important variables resulting from the gradient boosting algorithm for life satisfaction is presented in Table 3 (Supplementary Table S1 displays the list of variables with a relative influence higher than 0). The first ten variables were subjective poverty (r_s = -.35), self-perceived (good) health (r_s = .34), country (ω = .08), subjective survival probability (r_s = .28), neuroticism (r_s = -.25), total household income (r_s = .38), household type (ω = .03), extraversion (r_s = .17), reporting the fatigue criteria of frailty (ω = .06), and being ever diagnosed/currently having affective/emotional disorders (ω = .03). The pattern of differences across countries was similar to that for quality of life (see Supplementary Figure S1). Concerning household type, post-hoc tests revealed that participants living in a household that consists of a couple reported higher scores on satisfaction with life compared to people living single in a household or in a household that consists of several singles.

Table 3

Ranking of the Importance of the First Ten Variables According to Gradient Boosting Algorithm to Predict Quality of Life, Life Satisfaction, and Happiness

Quality of life	Relative Influence	Life satisfaction	Relative Influence	Happiness	Relative Influence
Subjective poverty	21.349	Subjective poverty	23.716	Country	17.003
Self-perceived health	15.375	Self-perceived health	19.475	Neuroticism (Big Five)	11.216
Mobility limitations	9.387	Country	12.688	Subjective poverty	7.592
Neuroticism (Big Five)	9.169	Subjective survival probability	11.999	Subjective survival probability	6.589
Subjective survival probability	7.913	Neuroticism (Big Five)	6.742	Group of friends felt comfortable spending time with (in childhood)	5.793
Country	7.880	Total household income	5.739	Marital status	5.787
Not bothered by frailty	5.774	Household type	3.035	Willingness to answer	5.703
Conscientiousness (Big Five)	3.164	Extraversion (Big Five)	2.053	Self-perceived health	4.763
Frequency of activities	3.163	Fatigue criteria of frailty	1.771	Extraversion (Big Five)	4.216
Limitations with instrumental activities of daily living	2.740	Ever diagnosed/currently having affective/emotional disorders	1.297	Total household income	4.066

4.3 Correlates of Happiness

Table 3 displays the order of the ten most important variables resulting from the gradient boosting algorithm for happiness (the list of variables with a relative influence higher than 0 is shown in Supplementary Table S1). In a diminishing order of importance, the first ten variables related to happiness were country (ω = .04), neuroticism (r_s = -.20), subjective poverty (r_s = -.20), subjective survival probability (r_s = .17), frequency with which participants had group of friends felt comfortable spending time with in childhood (r_s = .14), marital status (ω = .02), willingness to answer (ω = .03), self-perceived (good) health (r_s = .20), extraversion (r_s = .16), and total household income (r_s = .20). The pattern of differences across countries is displayed in Supplementary Figure S1. Consistent with the findings of life satisfaction and quality of life, happiness was higher among Central and Northern European countries compared to Southern/Mediterranean and Eastern European countries. Concerning marital status, post-hoc tests revealed that participants that are married and living with a spouse reported higher scores on happiness than participants that are in a registered partnership, married but not living with the spouse, never married, divorced, or widowed.

5. Discussion

Six categories of correlates (i.e., sociodemographic factors, personality, subjective life circumstances, activity, physical health, and childhood circumstances) were used in the analysis and Supplementary Figure S2 shows their importance for each outcome. Physical health and subjective life circumstances were the most important categories of correlates of quality of life and life satisfaction, while sociodemographic factors (for the most part country of residence) and psychological variables were the most important correlates of happiness.

The findings of the current study provide support for an appraised situational meaning theory of subjective well-being and quality of life among adults who are 50 years and older. The central assumption of all appraised situational meaning theories (e.g., Folkman & Moskowitz, 2000; Park, 2010) is that evaluations of events, not events themselves, explain why people have different responses to the same objective situation. Appraised situational meaning refers to the evaluation of the personal significance of life circumstances and the assignment of meaning to them. Indeed, the most important correlates of well-being and quality of life were subjective poverty rather than more "objective" indicators of the financial situation. By the same token, self-perceived health had a higher relative importance than any symptom or diagnosis of medical conditions. When making policy decisions, it is imperative to concentrate on policies that take into account subjective perceptions. For instance, to cope with subjective poverty, income enhancement through policy intervention may not be sufficient without an understanding of how and why the people feel poor.

Speaking of subjective appraisal, an important and unexpected finding of the present study concerns the relative influence of subjective survival probability in the model predicting the three outcomes. This relationship has been overlooked in the literature. It is, therefore, important for healthcare professionals to explore older people's perceptions of their life and future (including their subjective survival probability).

The results of the present study do not provide convincing evidence that objective life circumstances play a major role in determining subjective well-being and quality of life in later life. Therefore, the results of the present study failed to support the assumptions of stratification theory (George, 2010) which underlines the role of most advantaged life circumstances. The relative influence of gender, levels of education, and income was marginal or negligible. The low relative influence of income is in line with the findings of a previous meta-analysis of study which showed that the relationship between income and subjective well-being in later life is small, albeit significant (Pinquart & Sörensen, 2000). In addition, consistent with the findings of the present study, this meta-analysis revealed that the effect of education was less pronounced than that of income. Notwithstanding, the social structures and social processes that result in social and economic inequalities (e.g., differential allocation of assets and resources to members of a society) emphasized in stratification theory do play a role and can be considered distal predictors of subjective well-being and quality of life. It seems plausible to hypothesize that the influence of objective life circumstances on positive mental health outcomes may be mediated by the appraisal of the situation, its meaning and significance. In addition, older adults may adjust their needs and desires to fit their financial situation, and this may attenuate the relationship between income and positive mental health (Pinquart & Sörensen, 2000). Also, the effect of gender per se was negligible. Although previous studies have documented gender differences in quality of life and well-being among older adults (e.g., Gaymu & Springer, 2010; Matud et al., 2020; Molzahn et al., 2010), these gender differences may be explained by gender-related inequalities (e.g., socioeconomic status, health status, living conditions) embedded in patriarchal societies (e.g., Gaymu & Springer, 2010; Ko et al., 2019). Future research should examine potential mediators or moderators of the relation between life circumstances or inequalities and subjective well-being or quality of life in later life.

In the present study it was found that personality variables, mainly neuroticism, and secondarily, extraversion and conscientiousness, are associated with quality of life and subjective well-being. These findings are in line with a large body of research documenting substantial links between such personality traits and subjective well-being (e.g., Anglim et al., 2020). The association between personality and subjective well-being may be explained, in part, by genetic factors (e.g., Røysamb et al., 2018; Weiss et al., 2016). Notwithstanding, when taking into account the most recent findings in the literature, genetic influences explain 32–40 % of the variation and, therefore, subjective well-being can be considered not only heritable and stable, but also variable and changeable (Nes & Røysamb, 2017). As a practical implication, Røysamb et al. (2018) proposed individual and societal happiness-enhancing interventions, policies, activities, and environments are likely to be effective and longer lasting.

Support for the notion of variable subjective well-being is provided by the relative influence of country of residence. In addition, the important role of the country of residence provides support to the social indicators perspective (George, 2010) which focuses on cross-national differences in subjective well-being and quality of life in later life. The findings of the present study demonstrated that quality of life and subjective well-being vary substantially across European countries. These cross-national differences are similar to those obtained in studies involving the European general population (e.g., Huppert & So, 2013; Pierewan & Tampubolon, 2014), and therefore, such differences do not seem specific to adults who are 50 years and older. Specifically, people living in Northern Europe tend to report the highest rankings, followed by people living in Western, Southern, and Eastern Europe. A number of different explanations have been put forward to explain these cross-national differences among European countries, such as income inequality, social welfare, health care systems, employment rate, values, and social trust/capital (Diener et al., 2010; Huppert & So, 2013; Pierewan & Tampubolon, 2014). The findings of the present study suggest that policy and programs addressing inequality and improving social welfare and health care systems may be considered important factors for the well-being of older adults (Fulmer et al., 2021).

Results of the study revealed that social participation was associated with quality of life and, to a lesser extent, to happiness and life satisfaction. Although these findings provide some support for activity theory (Havighurst, 1961; Lemon et al., 1972) and are in line with the results of recent studies (e.g., Adams et al., 2011; Huxhold et al., 2014; Mackenzie & Abdulrazaq, 2021), the role of social participant was rather limited. The limited role of social participation warrants future research into the potential mediating and moderating factors that may explain and attenuate or amplify the effect of social participation and engagement in intentional activity (Adams et al., 2011; Sheldon & Lyubomirsky, 2007). In addition, it was found that it is not the participation in a specific activity that is important, but rather the impact of the frequency of participation in different activities. It is recommended to develop programs that can increase the frequency of participation in different activities.

The quality of childhood experiences has been hypothesized to have a significant impact in later life among adults (e.g., Martin, 2005; Wood et al., 2021). In the present study, the quality of parent–child relationships as well as relationships with peers and loneliness were the most important predictors. However, their relative influence was rather low.

5.1 Strengths and Limitations

These results should be interpreted in the light of the strengths and limitations of the study. First, the reliance on cross-sectional data precludes any conclusions regarding causality. Second, potential selection bias cannot be excluded. However, it should be noted that the overall response rate of SHARE is quite high compared to other European and US survey studies (Börsch-Supan et al., 2013). Third, data quality may be affected by response biases (e.g., social desirability bias). Notwithstanding, there is evidence that computer-assisted personal interviewing is associated with lower levels of social desirability bias (Schräpler et al., 2010). Fourth, many of the study variables were only assessed with one-item measures. Fifth, in the present study, an exploratory rather than hypothesis-testing approach was used. Therefore, results from machine learning research can be considered as hypothesis generating and should be validated in future replications with randomized controlled trials. Notwithstanding, machine learning could be considered a powerful tool for enhancing aging research (e.g., Chen, 2021; do Nascimento et al., 2022; Lee et al., 2020; Qin et al., 2020).

Despite the aforementioned limitations, key strengths of the present study include the use of a well-powered sample and the inclusion of 107 potential correlates. In addition, the novelty of the current study lies in the application of machine learning techniques to predict quality of life, happiness, and life satisfaction among European adults who are 50 years and older.

5.2 Conclusion

Despite the methodological limitations, the results of the present study highlight important correlates of quality of life, happiness, and life satisfaction among European adults who are 50 years and older and, thus, can contribute to a growing literature of successful aging. Specifically, the most important variables were subjective poverty, self-perceived health, country of residence, subjective survival probability, and personality factors (especially neuroticism). The role of social participation (activity) as well as childhood circumstances was less important. Sociodemographic factors (except for country of residence) were much less important.

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Conflict of Interest:

The author has no conflict of interest to declare.

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