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Predictors of Anxiety in Middle-Aged and Older European Adults: A Machine Learning Comparative Study

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Abstract: Anxiety in older adults is a prevalent yet under-recognized condition associated with significant societal and individual burdens. This study used a machine learning approach to compare the relative importance of 57 risk and protective factors for anxiety symptoms in a population-representative sample of middle-aged and older European adults (N = 65,684; ages 45–103 years; 55.7% women; 15 countries represented). The results revealed loneliness and self-rated poor health as primary risk factors (Nagelkerke R^2 = 0.272), with additional predictive contributions from country of residence, functional limitations, financial distress, and family care burden. Notably, follow-up analysis showed that none of the 16 social network variables were associated with loneliness; rather, cohabitating with a partner/spouse was most strongly associated with reduced loneliness. Further research is needed to elucidate directional associations between loneliness and anxiety (both general and sub-types). These findings underscore the imperative of addressing loneliness for mitigating anxiety and related mental health conditions among aging populations.

Keywords: generalized anxiety; loneliness; social isolation; social network; cognition; population; aging

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1. Introduction

Approximately 14% of older adults live with a mental health condition, of which anxiety-related disorders are the most common (Kessler et al. 2007; World Health Organization 2024). Prevalence estimates of clinically relevant anxiety symptoms in community-dwelling older adults reliably range between 5 and 6%. However, anxiety prevalence may be substantially higher (e.g., >20%) when taking into consideration adults living in assisted care facilities and the general tendency within this age demographic to under-report anxiety symptoms (Curran et al. 2020; Volkert et al. 2013; Witlox et al. 2021). Anxiety and depression together account for 11% of years lived with disability in later life, with a corresponding cost to the world economy currently estimated at over USD 1 trillion per year. This amount is projected to increase dramatically by 2030, concomitant with a growing global population of older adults (Lancet Global Health 2020).

Anxiety in later life is associated with decreased social and occupational functioning, disruption to daily activities, reduced quality of life, and increased risks for dementia and death (De Beurs et al. 1999; Lijster et al. 2017; Santabárbara et al. 2020). Although anxiety is a treatable condition, it remains under-diagnosed and under-treated relative to other mood disorders, such as depression (Weisberg 2009; Weisberg et al. 2014). Primary care visits, which occur with increasing frequency as people age, provide an opportunity to correct these shortfalls through enhanced screening and timely intervention. A clearer understanding of the differential importance of risk and protective factors implicated in later-life anxiety can facilitate these aims (Vink et al. 2008).

Systematic reviews have shown that anxiety in adulthood is linked with general poor health (e.g., as indicated by number of chronic disease conditions) and functional disability. There is also evidence that women, non-married persons, and individuals reporting higher occurrences of adverse childhood experiences and stressful life events are at elevated risk (Wolitzky-Taylor et al. 2010). In contrast to research on late-life depression (Cole and Dendukuri 2003), there have so far been few meta-analyses of anxiety-related risk and protective factors as manifest in community-dwelling older adults. Extant meta-analyses of anxiety in adulthood have more often focused on prevalence rates (Grenier et al. 2019).

In recent years, there has been a growing trend toward using machine learning (ML) approaches to compare risk/protective factors in large-sample behavioral epidemiology studies of older adults (Aichele et al. 2016; Aichele et al. 2017; Aschwanden et al. 2020; Choi et al. 2020; Puterman et al. 2020). An advantage of ML over conventional parametric techniques is that ML can capture non-linear and moderating effects in an exploratory way, i.e., without requiring the explicit specification of all possible interactions between variables. Additionally, ML methods may employ data and variable sub-selection routines as "built-in" cross-validation checks to mitigate problems related to multi-collinearity and spurious variable selection (model overfitting) in determining relative predictive importance (Handing et al. 2022)

Although ML has seen increasing use in applications to detect and differentially diagnose anxiety in both adolescents and adults, there have to date been few ML comparative studies of biological, psychological, and social predictors of anxiety in population-representative samples of middle-aged and older adults. (Li et al. 2024b) used ML to compare 2599 variables as predictors of anxiety onset in a cohort of 24,388 Canadian adults. The results showed that variables related to prior history of a mood disorder and frailty were top predictors (a comprehensive list of predictive associations was not provided). (Byeon 2021) used ML to compare demographic, social network and communication, neighborhood environment, and select mental health indices as predictors of anxiety disorders in a sample of 1558 South Korean older adults, with the results implicating loneliness, low self-esteem, and reduced communication with family members as key risk factors. Other ML studies with anxiety as a target outcome have focused more on comparing predictive accuracy across different ML algorithms than on substantive anxiety associations and so are not summarized here.

The current work is a companion study to (Handing et al. 2022), in which we used machine learning to compare socio-relational, health, lifestyle, cognitive, and functional limitation variables as predictors of depression risk in participants in the Survey of Health, Ageing, and Retirement in Europe (SHARE). The current analyses were applied to data from SHARE Wave 5 (N = 65,684; ages 45–103 years; 55.7% women; 15 countries represented). Anxiety symptoms were assessed using items from the Beck Anxiety Inventory (BAI) (Beck et al. 1988). Fifty-seven risk/protective factors were compared. The analytical approach leveraged a split-sample methodology, wherein random forest machine learning (RFML) (Strobl et al. 2009) was first applied to one subset of the data in order to rank the risk/protective factors by predictive strength and generalized linear regression (GLR) was then applied to the second subset of observations to estimate effect sizes with respect to a known statistical distribution and also as a cross-method confirmatory check of the results. It was anticipated that chronic health conditions, functional limitations, and variables indicative of social isolation would stand out as the most salient risk factors for elevation of anxiety symptoms.

2. Materials and Methods

Descriptions of the Materials and Methods have been adapted from our prior companion study (Handing et al. 2022), which focused on a different outcome variable and SHARE study wave (sample group), but which used similar predictor variables and a similar (but not identical) analytical approach.

2.1. Study Design and Population

Data for the study were sourced from Wave 5 of SHARE, a multi-national (14 European countries and Israel) study of middle-aged and older adults (N = 65,684; ages 45–103 years;

55.7% women). The SHARE participant sample and study design are described in (Börsch-Supan et al. 2013) and (SHARE-ERIC 2024). Assessments were conducted via Computer Assisted Personal Interview (CAPI) supplemented by paper-and-pencil questionnaires. The survey items included demographic, socio-relational, economic, and health-related measures. Interviews were conducted in respondents' homes, and they took approximately 90 min. SHARE used probabilistic sampling based on household (and other) demographic information to ensure that participant selection was nationally representative.

Across countries, household response rates for SHARE Wave 5 ranged from 32.7% (Luxembourg) to 67.5% (Israel) (Bergmann et al. 2017). Identified households included at least one person (primary respondent) aged 50 years or older and, if present, their partners, who could be of any age. Here, we imposed an inclusion cutoff age of 45 years to capture a broader range of middle-aged adults (observations at younger ages were sparse). Wave 5 was selected as a focus because both anxiety and self-reported loneliness using a harmonized measure (see below) were only available at that wave.

The SHARE study undergoes continuous ethical review. For Waves 1 to 4, SHARE was reviewed and approved by the Ethics Committee of the University of Mannheim. Later SHARE Waves were reviewed and approved by the Ethics Council of the Max Planck Society. Additionally, country-specific implementations of SHARE were reviewed and approved by the respective ethics committees or institutional review boards as required. The reviews covered all aspects of the SHARE study, including sub-projects and compliance with relevant legal norms and international ethical standards. Further information can be found at https://share-eric.eu/data/faqs-support (accessed 11 November 2024).

2.2. Measures

2.2.1. Anxiety

Anxiety was measured by five items from the Beck Anxiety Inventory (Beck et al. 1988). The BAI was developed to assess anxiety symptoms independently of depression. Its psychometric properties are well established, and it shows high internal consistency in its original form and also as the brief 5-item assessment used in SHARE (Cronbach's alpha = 0.71) (Bardhoshi et al. 2016; Chlapecka et al. 2023). The items, which assessed anxiety symptoms experienced during the past week, were as follows: "I had fear of the worst happening", "I was nervous", "I felt my hands trembling", "I had a fear of dying", and "I felt faint". Items were answered on a 4-point Likert scale: 1 = "never", 2 = "hardly ever", 3 = "some of the time", and 4 = "most of the time". Individual composite scores for anxiety were calculated as the average response across these items, multiplied by 5 (for consistency with summation score scaling when based on complete data).

2.2.2. Risk/Protective Factors

Data for these analyses were primarily obtained from easySHARE, a curated subset of SHARE variables that have been thoroughly screened. These measures were augmented with other Wave 5 variables related to behavioral risk factors, interpersonal transactions, and health. Additionally, social network variables which were only available at Waves 4 and 6 were included (as the average response across waves) for consistency with our prior SHARE study on depression (Handing et al. 2022). These variables have been carefully documented by SHARE, https://share-eric.eu/data/data-documentation (accessed 15 June 2024).

2.2.3. Demographics, Home Environment, and Personal Finance

Analyses included 6 sociodemographic variables: biological sex, chronological age, education level (based on the International Standard Classification of Education) (Schneider 2013), employment status, marital status, and country of residence. Home and finance variables included number of people in the household, household annual income (in euros), self-rated financial distress, and neighborhood disorder. Self-rated financial distress was based on the question, "Thinking of your household's monthly income, would you say that your household is able to make ends meet?" Neighborhood disorder was calculated as the average response to four items: "I really feel part of this area", "Vandalism/crime is a big problem here", "The area is kept very clean", and "If I were in trouble, there are people in this area who would help me", reverse-coded as applicable such that higher scores represented more neighborhood disorder.

2.2.4. Family Configuration, Social Network, and Care-Related Transfers

In addition to marital status (categorized with general demographics), analyses included 9 variables related to family configuration and responsibilities: cohabitation with spouse/partner; number of children and number of grandchildren; residential proximity to children; mortality statuses of parents and siblings; and an item to gauge whether family responsibilities prevented respondents from pursuing personal interests (here interpreted as "family care burden"). Additionally, 16 social network variables assessed the number of persons in the network by physical proximity, by frequency of contact, by biological sex, by family member type, and by emotional closeness, as well as summary measures of emotional closeness, frequency of contact, physical distance to network members, and overall (composite) social connectedness (Litwin and Stoeckel 2015). Care-related activity was assessed by whether respondents had given/received financial support (EUR > 250) in the past year, provided/received care from others living outside the home, provided regular personal care inside the home, and/or looked after grandchildren without the parents present.

2.2.5. Health and Functional Limitations

The analyzed data included 13 measures of health, including lifestyle and functional ability. These were as follows: number of chronic diseases, self-rated poor health, diagnoses of hypertension and diabetes, body mass index, (lack of) physical activity, tobacco smoking, and alcohol consumption. The presence (diagnosis) of the following medical conditions were aggregated in deriving the total number of chronic diseases: heart attack, hypertension, high blood cholesterol, stroke and/or cerebrovascular disease, diabetes, chronic lung disease, cancer, stomach or duodenal ulcer, Parkinson's disease, cataracts, and hip and/or femoral fracture. Functional health was assessed as maximum grip strength and four composite scores: difficulties in activities of daily living (ADL; dressing oneself, bathing/showering, eating/cutting up food, walking across a room, and getting out of bed), difficulties in instrumental activities of daily living (IADL; making telephone calls, taking medications, and managing money), difficulties with fine motor skills (picking up a small coin, eating/cutting up food, and dressing), and difficulties with mobility (walking 100 m, walking across a room, climbing several flights of stairs, and climbing one flight of stairs).

2.2.6. Cognition and Mental Health

Cognitive measures were numerical ability (serial subtraction) and delayed verbal recall memory (of a 10-item word list). Loneliness was assessed using the UCLA-3 Loneliness Scale (Hughes et al. 2004): "lack of companionship", "feel left out", "feel isolated from others", and one additional item: "feel lonely". Depressive symptoms were not included due to potential overlap with anxiety symptoms (the dependent measure for the study).

2.3. Data Analysis

All analyses were conducted within the R statistical computing environment (R Core Team 2024). The data were split into analysis groups (A1 = random forest machine learning, or RFML; A2 = generalized linear regression, or GLR) using R's built-in random sampling function, with two-thirds of observations assigned to A1 and one-third to A2. A1 observations were further subdivided such that two-thirds were used for machine learning parameter tuning and one-third were used for testing. This resulted in two sub-samples for the RFML analysis, A1.tune (n = 29,193) and A1.test (n = 14,596), and one sub-sample for the

GLR analysis: A2 (n = 21,895). Missing values were imputed using the R software package mice (multiple imputation by chained equations) (Van Buuren and Groothuis-Oudshoorn 2011). A single complete data set was imputed for RFML analyses (which simply provide a rank ordering of variables by predictive importance), whereas 20 complete data sets were imputed for generalized linear regression analysis (with estimates pooled across analyses of the data sets).

2.3.1. Random Forest Machine Learning (RFML)

RFML is a machine learning approach related to classification and regression trees (Breiman 2001). Regression trees recursively partition observations into sub-groups by predictor selection criteria that maximally discriminate differences in an outcome variable (e.g., anxiety symptoms). Trees are able to account for complex interactions between predictors in rankings of predictive importance, and they are also able to approximate both linear and non-linear effects by means of several splits within a given predictor. RFML expands upon the single tree approach to provide built-in cross-validation: Multiple trees are generated using randomly sampled subsets of observations and predictors. RFML variable importance (VIMP) measures implicitly capture linear, non-linear, and higher-order interaction effects. Problems related to multi-collinearity and spurious variable selection are mitigated.

RFML was applied to the A1 sub-samples using the R package party, with the "cforest_unbiased" option for predictors of mixed types and VIMP calculated using the permutation feature method (Strobl et al. 2007; Strobl et al. 2009). Feature tuning was applied to the parameters ntree (number of trees) and mtry (number of variables pre-sampled per node). The recommended default values for these parameters, with p = number of predictors, are $2p$ (ntree) and $\sqrt{p}$ (mtry), which here would give ntree = 114 and mtry = 8, respectively. Tuning values for ntree were thus selected as ranging from 100 to 600 (in increments of 100) and for mtry from 8 to 13. The predictive accuracy (mean absolute error) for each combination of tuning parameters was calculated using the out-of-bag observations (OOBs; unsampled observations during tree/forest construction). The "test" RFML was then run using the identified optimal tuning parameter values to obtain variable importance (VIMP) estimates and predictor rankings.

2.3.2. Generalized Linear Regression (GLR)

Stepwise GLR was applied to the A2 data, with a gamma distribution selected for the outcome (given the positive skew in anxiety symptoms). Predictors were entered in decreasing order of VIMP, as determined from the RFML. Nagelkerke's pseudo-R-square ($R^2{}_{\mathrm{Nk}}$) (Nagelkerke 1991) was used to approximate explained variation in anxiety accounted for by each predictor. A priori sensitivity analysis (α = 0.05, β = 0.80, N = 20,000) indicated that a stepwise change in R^2 (ΔR^2) < 0.0005 could reliably be detected. In terms of explained variance (interpretation), this value was exceedingly small, so a threshold of $\Delta R^2{}_{\mathrm{Nk}} = 0.005$ (one magnitude larger) was selected for predictor retention. Parameter estimates were pooled across analyses of the imputed data sets using Rubin's rule as implemented in R package mice (Van Buuren and Groothuis-Oudshoorn 2011). These were exponentiated to further aid interpretation. Point estimates for $\Delta R^2{}_{\mathrm{Nk}}$ and cumulative $R^2{}_{\mathrm{Nk}}$ were obtained by averaging across analyses of the imputed data sets.

3. Results

3.1. Summary Statistics

Figure 1 shows the distribution of anxiety symptom scores. Anxiety data were missing for only 2.0% of participants. Approximately 10% of SHARE participants showed severe ($\geq$12) symptom counts, as previously reported (Chlapecka et al. 2023). Summary statistics for all risk/protective factors in the current analyses are provided in Table 1. Response rates (non-missingness) for all wave five variables have previously been provided by SHARE (SHARE-ERIC 2024) and so are not presented here to conserve space. As noted above, social network variables were only assessed at Waves 4 and 6, scores for which were averaged here for Wave 5 participants (86.2% of whom were present at Wave 4 and/or Wave 6).

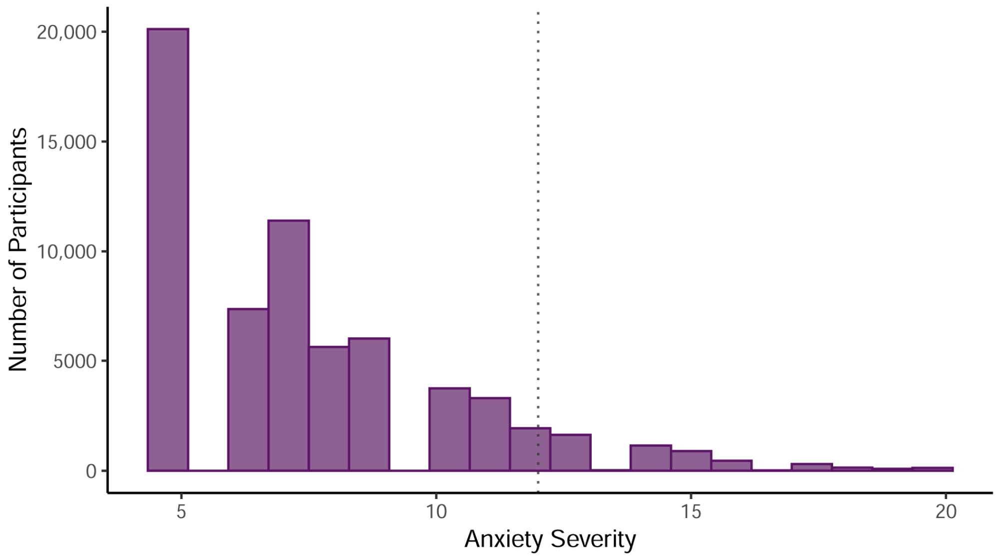

Figure 1. Distribution of composite anxiety scores (based on five items, each scaled from 1 to 4; higher levels = greater severity). The dotted vertical line shows the threshold for severe anxiety symptoms (≥12).

Table 1. Sample descriptive statistics of variables included in analyses.

Demographics (N = 65,684)	Summary Statistics
1. Women	n = 36,563 (55.7%)
2. Age in years	Mdn = 65.9, range = (45.0, 103.5)
3. Education level	
None	n = 3026 (4.6%)
Primary	n = 10,683 (16.3%)
Lower secondary	n = 11,889 (18.1%)
Upper secondary	n = 21,163 (32.2%)
Post-secondary	n = 2945 (4.5%)
First-stage tertiary	n = 14,231 (21.7%)
Second-stage tertiary	n = 590 (0.9%)
4. Employment status	
Retired	n = 36,590 (55.7%)
Employed or self-employed	n = 18,023 (27.4%)
Unemployed	n = 1868 (2.8%)
Permanently sick/disabled	n = 2313 (3.5%)
Homemaker	n = 5244 (8.0%)
5. Marital status	
Married and living w/spouse	n = 44,825 (68.2%)
Registered partnership	n = 964 (1.5%)
Separated	n = 769 (1.2%)
Never married	n = 3615 (5.5%)
Divorced	n = 5673 (8.6%)
Widowed	n = 9403 (14.3%)
6. Country or residence (15 countries; ns not reported to preserve space)	
Home and personal finance	
7. No. of people in household	Mdn = 2.0, IQR = (2.0, 2.0)
8. Household income in EUR (*1k)	Mdn = 24,877, IQR = (14.5; 42.4)
9. Financial distress [1]	Mdn = 2.0, IQR = (1.0, 3.0)
10. Neighborhood disorder	Mdn = 3.2, IQR = (3.0, 3.8)

Table 1. *Cont.*

Family	
11. Living with partner/spouse	n = 48,072 (73.2%)
12. No. of children	Mdn = 2.0, IQR = (1.0, 3.0)
13. No. of grandchildren	Mdn = 2.0, IQR = (1.0, 4.0)
14. ≥1 child in same household	n = 15,915 (24.2%)
15. ≥1 child lives <1 km away	n = 22,184 (33.8%)
16. Mother still alive	n = 14,408 (21.9%)
17. Father still alive	n = 5898 (9%)
18. No. of siblings still alive	Mdn = 2.0, IQR = (1.0, 3.0)
19. Burden of family responsibilities [1]	M = 1.8, SD = 1
Social network	
20. Size of social network	Mdn = 2.5, IQR = (1.5, 3.5)
21. No. of SNMs in daily contact	Mdn = 1.0, IQR = (1.0, 1.5)
22. No. of SNMs in weekly contact	Mdn = 2.0, IQR = (1.0, 3.0)
23. No. of family members in SN	Mdn = 2.0, IQR = (1.0, 3.0)
24. No. of women in SN	Mdn = 1.0, IQR = (1.0, 2.0)
25. No. of men in SN	Mdn = 1.0, IQR = (0.0, 1.5)
26. Avg. proximity of SNMs	M = 3.2, SD = 1.5
27. Proximity of closest SNMs	M = 1.9, SD = 1.4
28. No. of SNMs within 1 km	M = 1.2, SD = 0.9
29. No. of SNMs within 5 km	M = 1.6, SD = 1
30. Avg. freq. of contact from SNMs	M = 1.9, SD = 0.9
31. Freq. contact with closest SNMs	M = 1.3, SD = 0.7
32. Avg. emotional closeness to SNMs	M = 3.3, SD = 0.6
33. Emotional closeness to closest SNMs	M = 3.6, SD = 0.6
34. No. of very emotionally close SNMs	Mdn = 2.0, IQR = (1.0, 3.0)
35. Social connectedness	M = 2, SD = 0.9
Care-related transfers (past year)	
36. Received support of EUR > 250	n = 3558 (5.4%)
37. Received outside help	n = 12,314 (18.7%)
38. Gave support of EUR > 250	n = 13,104 (20%)
39. Gave regular care in-home	n = 4425 (6.7%)
40. Gave help outside home	n = 12,917 (19.7%)
41. Gave care for grandchildren	n = 14,322 (21.8%)
Health and functional limitations	
42. No. of chronic diseases	M = 1.2, SD = 1.2
43. Self-rated poor health	M = 3.1, SD = 1.1
44. Hypertension diagnosis	n = 25,800 (39.3%)
45. Diabetes diagnosis	n = 8400 (12.8%)
46. Body mass index	M = 26.8, SD = 4.7
47. Lack of physical activity	M = 2.6, SD = 1.3
48. Ever smoked daily	n = 29,661 (45.2%)
49. Alcohol consumption frequency	M = 3.4, SD = 2.2
50. Maximum grip strength	M = 33.7, SD = 11.8
51–54. Difficulties in:	
Activities of daily living (ADL)	M = 0.2, SD = 0.8
Instrumental activities (IADL)	M = 0.1, SD = 0.5
Fine motor skills	M = 0.2, SD = 0.5
Mobility	M = 0.5, SD = 1.0
Cognition and mental health	
55. Numerical ability	M = 4.1, SD = 1.5
56. Delayed recall memory	M = 3.9, SD = 2.2
57. Loneliness	M = 1.3, SD = 0.4
OC. Anxiety symptoms	M = 7.6, SD = 2.9

Note: Predictors are numbered. OC = "outcome". IQR = interquartile range. [1] Items were reverse-coded from their original SHARE scaling to aid interpretation.

3.2. Random Forest Machine Learning

RFML parameter tuning results showed diminishing returns (reductions in mean absolute error < 0.001) beyond ntree = 300 and mtry = 11, so those parameter values were selected for the RFML test run. The results from the latter (variable importance rankings) are shown in Figure 2. The top predictors were loneliness, self-reported poor health, and country of residence. Additional predictors of note were related to functional health (mobility problems, difficulties in ADL, and grip strength), financial distress, family care burden, frequency of alcohol consumption, numerical ability, and neighborhood disorder.

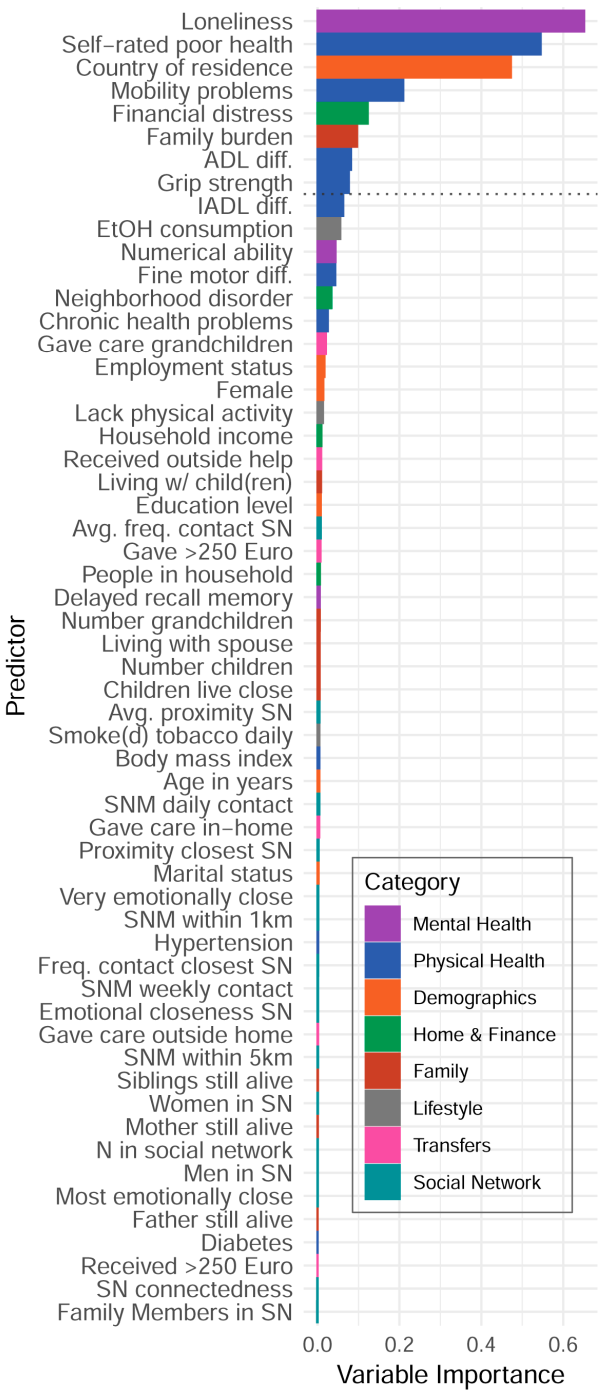

Figure 2. RFML results of predictors' variable importance (VIMP) in decreasing order. SN = social network (members). The dotted horizontal line marks the point below which all remaining predictors contributed <0.5% to explained variation in anxiety symptoms.

3.3. Generalized Linear Regression

Parameter estimates and R^2_{Nk} values for the GLR are presented in Table 2. Predictors for the GLR were entered stepwise in decreasing order of VIMP, with predictor retention determined by $\Delta R^2_{\mathrm{Nk}} \geq 0.005$. Only seven predictors met this threshold. Although difficulties in ADL was ranked sixth in terms of VIMP, the corresponding ΔR^2_{Nk} in the GLR was only 0.002, so it was removed from the model. Loneliness and self-rated poor health accounted for most of the explained variation in anxiety symptoms (cumulative $\Delta R^2_{\mathrm{Nk}} = 0.272$). Country of residence, mobility difficulties, financial distress, family burden, and grip strength accounted for an additional $\Delta R^2_{\mathrm{Nk}} = 0.092$, for a total $\Delta R^2_{\mathrm{Nk}} = 0.364$ (moderately strong prediction). Directions of effects were as anticipated, with loneliness, self-rated poor health, mobility problems, financial distress, and family burden all predicting increased anxiety symptoms and better grip strength predicting reduced anxiety symptoms. The countries with the highest levels of anxiety were Luxembourg, Israel, and the Czech Republic. The countries with the lowest levels of anxiety were Estonia, The Netherlands, and Sweden.

Table 2. Estimates from the generalized linear regression model.

	Estimates (Unstandardized)			Estimates (Standardized)		R^2_{Nk}	
Predictor	**B**	**S.E.**	**B.Exp**	**β**	**β.Exp**	**Stepwise**	**Cumulative**
(Intercept)	1.560	0.028	4.761	2.019	7.530		
Loneliness	0.172	0.005	1.187	0.077	1.081	0.169	0.169
Self-rated poor health	0.069	0.002	1.071	0.075	1.078	0.103	0.272
Country of residence [a]						0.044	0.316
Austria	−0.004	0.010	0.996	−0.001	0.999		
Sweden	−0.105	0.010	0.901	−0.027	0.973		
Netherlands	−0.111	0.010	0.895	−0.028	0.973		
Spain	0.048	0.010	1.050	0.014	1.015		
Italy	−0.033	0.010	0.967	−0.009	0.992		
France	−0.038	0.010	0.963	−0.010	0.991		
Denmark	−0.068	0.011	0.935	−0.016	0.984		
Switzerland	−0.023	0.012	0.977	−0.005	0.995		
Belgium	0.018	0.010	1.018	0.005	1.005		
Israel	0.050	0.013	1.052	0.010	1.010		
Czech Republic	0.050	0.010	1.051	0.014	1.014		
Luxembourg	0.092	0.014	1.096	0.014	1.015		
Slovenia	−0.033	0.012	0.967	−0.007	0.993		
Estonia	−0.112	0.010	0.894	−0.031	0.970		
Mobility problems	0.049	0.003	1.050	0.048	1.049	0.019	0.335
Financial distress	0.036	0.002	1.037	0.036	1.036	0.010	0.345
Family burden	0.038	0.002	1.039	0.036	1.037	0.011	0.356
Grip strength	−0.003	0.000	0.997	−0.037	0.963	0.009	0.364
Biological sex (female)	−0.003	0.006	0.997	−0.001	0.999	0.000	0.364
Age in years	0.000	0.000	1.000	−0.004	0.996	0.000	0.364

Note: The model assumed a gamma-distributed outcome with log link. Only variables that contributed more than 0.005 in stepwise change in Nagelkerke's pseudo-R^2 (ΔR^2_{Nk}) were included in the final model. Estimates (standardized) = predictors were standardized but the dependent variable was not. Non-significant estimates ($p < 0.005$) are shown italicized. [a] Germany was the reference (intercept) country.

3.4. Follow-Up Analyses: Predictors of Loneliness

To aid interpretation of the above results, follow-up analyses (employing the same methodology) were applied to self-reported loneliness as an outcome. The results showed that the strongest predictive effects were living with one's spouse/partner ($B = -0.185$, S.E. = 0.005, stepwise $\Delta R^2_{\mathrm{Nk}} = 0.110$), self-rated poor health ($B = 0.048$, S.E. = 0.002, $\Delta R^2_{\mathrm{Nk}} = 0.081$), and family care burden ($B = 0.043$, S.E. = 0.002, $\Delta R^2_{\mathrm{Nk}} = 0.026$). Additional analyses that included age and biological sex as moderators of loneliness and self-rated health effects showed that these interaction terms were very weakly associated with anxiety ($\Delta R^2_{\mathrm{Nk}} < 0.001$).

4. Discussion

Fifty-seven risk and protective factors were compared as predictors of anxiety symptoms in a population-representative sample of middle-aged and older European adults. Combined results from random forest machine learning (RFML) and generalized linear regression (GLR) analyses showed that loneliness and self-rated poor health were top predictors of anxiety symptoms, with a cumulative $R^2_{\mathrm{Nk}} = 0.272$. Additional notable contributors were country of residence (anxiety was highest in Luxembourg, the Czech Republic, and Israel and lowest in Estonia, The Netherlands, and Sweden), functional limitations (more mobility problems and lower grip strength predicted increased anxiety), and financial distress and family care burden (both predicted increased anxiety). With the inclusion of these latter predictors, the cumulative $R^2_{\mathrm{Nk}} = 0.364$. Biological sex and age were not predictive of differences in anxiety, nor did they moderate associations between the most salient risk/protective factors and anxiety.

These outcomes are consistent with prior summary reports of research on anxiety in later adulthood, which identified poor health and functional limitations as key risk factors (Vink et al. 2008; Wolitzky-Taylor et al. 2010). They are also consistent with one of very few prior machine learning studies of anxiety predictors in community-dwelling older adults, which similarly identified loneliness as a primary risk factor (Byeon 2021). Additionally, the most salient risk/protective factors observed in the current study are nearly identical to those observed in our prior machine learning study that focused on depression in SHARE participants. While other large-sample studies have similarly shown that loneliness is linked with both depression and anxiety (Domènech-Abella et al. 2019; Steen et al. 2022), the current results more clearly emphasize the comparative importance (i.e., relative strength of association) of loneliness for predicting anxiety in later adulthood.

Loneliness levels in many countries have been increasing over the past decades, with especially high levels observed in the United States (Infurna et al. 2024). In a National Academies of Sciences report (National Academies of Sciences Engineering and Medicine et al. 2020), over 25% of community-dwelling Americans aged 65 and older were found to be socially isolated, with 43% reporting feeling lonely. Summarizing topical research on loneliness, a recent *Scientific American* article recommended "reaching out to friends that you've left behind, doing volunteer work, taking up that hobby that you've been putting off, reading books or exercising in group settings" as ways to mitigate loneliness (Novak 2024). However, the current analyses showed that none of the 16 social network variables were predictive of differences in loneliness; rather, living with one's partner/spouse was the single most important predictor of loneliness. This suggests that, for European adults, having a "significant other" living in close proximity may be more important than other socio-relational features in shaping mental health following middle age. In terms of clinical implications, accounting for unmet close relational needs may be especially important in diagnosing and treating anxiety in later adulthood. To this end, there is some evidence to suggest that group mental health interventions, such as reminiscence and cognitive behavioral therapies, may be helpful (Elias et al. 2015; Smith et al. 2021). Whether broad "anti-loneliness" campaigns beneficially influence mental health outcomes in populations of older adults remains uncertain (Li et al. 2024a).

Variation in anxiety symptoms was also observed across countries, indicating that country-level attributes may further influence anxiety directly and/or by moderating the effects of individual factors like loneliness and poor physical health. For instance, individuals with chronic illnesses and limited personal care but who live in countries with expansive healthcare accessibility may experience fewer anxiety symptoms than similarly affected individuals who lack access to such social resources (Ding et al. 2023). Elevated anxiety levels have been reported in comparatively prosperous countries with high urban densities and socioeconomic pressures, which may intensify stress and mental health challenges (Javaid et al. 2023). Differences in social norms, such as cultural attitudes toward aging, may also underlie differences in anxiety (as well as in loneliness) (Infurna et al. 2024; Ridley et al. 2020). Policies supporting access to age-friendly housing and age-friendly city planning may also reduce anxiety risk (Liu et al. 2023). Socio-political shifts (Smith et al. 2024), environmental catastrophes (Garfin et al. 2022), and health pandemics (Gosselin et al. 2022) may differentially impact anxiety levels among individuals living in different countries. Such national-level factors were beyond the scope of this study, but they merit examination in future multi-modal investigations of anxiety in older adults.

It will also be important to examine dynamic (time-ordered) bidirectional associations between anxiety and loneliness given that each may influence the other by different mechanisms. Established evidence indicates that elevated social anxiety can lead to increased loneliness (Eres et al. 2021; Lim et al. 2016). The current results implicating personal financial pressures, functional limitations, and poor health further suggest various possible ways in which anxiety, more generally, may promote loneliness, e.g., prioritizing work over relational engagements due to financial anxiety and remaining isolated at home due to fear of falling or fear of disease transmission (Witlox et al. 2021; Gaeta and Brydges 2022). Conversely, loneliness may act as a precursor to anxiety, such as by mediating associations between needs for socio-emotional support (and/or personal care) and elevated anxiety levels. As this was a cross-sectional study, temporal directionality could not be tested. However, there is some evidence that loneliness–anxiety associations are indeed bidirectional, with stronger effects for loneliness as an originating influence (Domènech-Abella et al. 2019). Additional longitudinal investigations of loneliness–anxiety associations in older adults are needed to clarify specific mechanistic associations.

Beyond limitations related to directionality of associations, the anxiety measure used for the current study lacked specificity that could have allowed for more nuanced interpretation (i.e., risk factors corresponding to specific anxiety sub-types). Cognitive measures were constrained to those that could be administered via brief screening, which may be why stronger anxiety–cognition associations were not observed (e.g., measures of executive function, such as response inhibition, were lacking) (Beaudreau and O'Hara 2009). The strengths of the study are its large, population-representative participant sample, its inclusion of a broad range of risk/protective factors, and the machine learning methodology that allowed for comprehensive comparison of predictive effects.

5. Conclusions

Comparative studies of risk and protective factors for generalized anxiety in later adulthood remain lacking in the empirical literature, especially when contrasted with research on late-life depression. The current comparative analyses show that loneliness and self-rated health strongly eclipse other risk and protective factors for predicting anxiety in middle-aged and older European adults.

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Institutional Review Board Statement: The SHARE study undergoes continuous ethical review. For Waves 1 to 4, SHARE was reviewed and approved by the Ethics Committee of the University of Mannheim. Later SHARE Waves were reviewed and approved by the Ethics Council of the Max Planck Society. Additionally, country-specific implementations of SHARE were reviewed and approved by the respective ethics committees or institutional review boards as required. The reviews covered all aspects of the SHARE study, including sub-projects and compliance with relevant legal norms and international ethical standards. Further information can be found at https://share-eric.eu/data/faqs-support.

Informed Consent Statement: The relevant local research ethics committees in the participating countries approved SHARE. All participants provided written informed consent.

Data Availability Statement: This study used data from the Survey of Health, Ageing and Retirement in Europe, which is freely available to academic researchers (http://www.share-project.org, accessed 15 July 2021). Data and computer codes specific to the current analyses will be provided to interested parties (who have completed the SHARE data use agreement) upon request to the author.

Conflicts of Interest: The author declares no conflicts of interest.

References

Aichele, Stephen, Patrick Rabbitt, and Paolo Ghisletta. 2016. Think fast, feel fine, live long: A 29-year study of cognition, health, and survival in middle-aged and older adults. *Psychological Science* 27: 518–29. [CrossRef] [PubMed]

Aichele, Stephen, Patrick Rabbitt, and Paolo Ghisletta. 2017. Illness and intelligence are comparatively strong predictors of individual differences in depressive symptoms following middle age. *Aging and Mental Health* 23: 122–31. [CrossRef] [PubMed]

Aschwanden, Damaris, Stephen Aichele, Paolo Ghisletta, Antonio Terracciano, Matthias Kliegel, Angelina R. Sutin, Justin Brown, and Mathias Allemand. 2020. Predicting cognitive impairment and dementia: A machine learning approach. *Journal of Alzheimer's Disease* 75: 717–28. [CrossRef] [PubMed]

Bardhoshi, Gerta, Kelly Duncan, and Bradley T. Erford. 2016. Psychometric meta-analysis of the English version of the Beck Anxiety Inventory. *Journal of Counseling & Development* 94: 356–73. [CrossRef]

Beaudreau, Sherry A., and Ruth O'Hara. 2009. The association of anxiety and depressive symptoms with cognitive performance in community-dwelling older adults. *Psychology and Aging* 24: 507. [CrossRef]

Beck, Aaron T., Norman Epstein, Gary Brown, and Robert A. Steer. 1988. An inventory for measuring clinical anxiety: Psychometric properties. *Journal of Consulting and Clinical Psychology* 56: 893. [CrossRef]

Bergmann, Michael, Thorsten Kneip, Giuseppe De Luca, and Annette Scherpenzeel. 2017. *Survey Participation in the Survey of Health, Ageing and Retirement in Europe (SHARE)*. Wave 1–6. Munich: Munich Center for the Economics of Aging.

Börsch-Supan, Axel, Martina Brandt, Christian Hunkler, Thorsten Kneip, Julie Korbmacher, Frederic Malter, Barbara Schaan, Stephanie Stuck, and Sabrina Zuber. 2013. Data resource profile: The Survey of Health, Ageing and Retirement in Europe (SHARE). *International Journal of Epidemiology* 42: 992–1001. [CrossRef]

Breiman, Leo. 2001. Random forests. *Machine Learning* 45: 5–32. [CrossRef]

Byeon, Haewon. 2021. Exploring factors for predicting anxiety disorders of the elderly living alone in South Korea using interpretable machine learning: A population-based study. *International Journal of Environmental Research and Public Health* 18: 7625. [CrossRef]

Chlapecka, Adam, Katrin Wolfová, Barbora Fryčová, and Pavla Cermakova. 2023. Educational attainment and anxiety in middle-aged and older Europeans. *Scientific Reports* 13: 13314. [CrossRef]

Choi, Karmel W., Murray B. Stein, Kristen M. Nishimi, Tian Ge, Jonathan R. I. Coleman, Chia-Yen Chen, Andrew Ratanatharathorn, Amanda B. Zheutlin, Erin C. Dunn, 23andMe Research Team, and et al. 2020. An exposure-wide and Mendelian randomization approach to identifying modifiable factors for the prevention of depression. *American Journal of Psychiatry* 177: 944–54. [CrossRef] [PubMed]

Cole, Martin G., and Nandini Dendukuri. 2003. Risk factors for depression among elderly community subjects: A systematic review and meta-analysis. *American Journal of Psychiatry* 160: 1147–56. [CrossRef] [PubMed]

Curran, Emma, Michael Rosato, Finola Ferry, and Gerard Leavey. 2020. Prevalence and factors associated with anxiety and depression in older adults: Gender differences in psychosocial indicators. *Journal of Affective Disorders* 267: 114–22. [CrossRef] [PubMed]

De Beurs, Edwin, A. T. F. Beekman, A. J. L. M. Van Balkom, D. J. H. Deeg, and W. Van Tilburg. 1999. Consequences of anxiety in older persons: Its effect on disability, well-being and use of health services. *Psychological Medicine* 29: 583–93. [CrossRef] [PubMed]

Ding, Shuo, Guoqing Liu, Fuqin Xu, Kai Ji, Lanlan Zhao, Xin Zheng, Otsen Benjamin, Zhengsheng Wang, Shufan Yang, and Ren Chen. 2023. The satisfaction of elderly people with elderly caring social organizations and its relationship with social support and anxiety during the COVID-19 pandemic: A cross-sectional study. *BMC Public Health* 23: 1206. [CrossRef]

Domènech-Abella, Joan, Jordi Mundó, Josep Maria Haro, and Maria Rubio-Valera. 2019. Anxiety, depression, loneliness and social network in the elderly: Longitudinal associations from The Irish Longitudinal Study on Ageing (TILDA). *Journal of Affective Disorders* 246: 82–88. [CrossRef]

Elias, Sharifah M. S., Christine Neville, and Theresa Scott. 2015. The effectiveness of group reminiscence therapy for loneliness, anxiety and depression in older adults in long-term care: A systematic review. *Geriatric Nursing* 36: 372–80. [CrossRef]

Eres, Robert, Michelle H. Lim, Steven Lanham, Christopher Jillard, and Glen Bates. 2021. Loneliness and emotion regulation: Implications of having social anxiety disorder. *Australian Journal of Psychology* 73: 46–56. [CrossRef]

Gaeta, Laura, and Christopher R. Brydges. 2022. Coronavirus-related anxiety, social isolation, and loneliness in older adults in Northern California during the stay-at-home order. In *The COVID-19 Pandemic and Older Adults*. Edited by C. M. Brown. London: Routledge, pp. 21–32.

Garfin, Dana Rose, Rebecca R. Thompson, E. Alison Holman, Gabrielle Wong-Parodi, and Roxane Cohen Silver. 2022. Association between repeated exposure to hurricanes and mental health in a representative sample of Florida residents. *JAMA Network Open* 5: e2217251. [CrossRef]

Gosselin, Patrick, Camille Castonguay, Marika Goyette, Rosemarie Lambert, Mallorie Brisson, Philippe Landreville, and Sébastien Grenier. 2022. Anxiety among older adults during the COVID-19 pandemic. *Journal of Anxiety Disorders* 92: 102633. [CrossRef]

Grenier, Sébastien, Marie-Christine Payette, Bruno Gunther, Sorayya Askari, Frédérique F. Desjardins, Béatrice Raymond, and Djamal Berbiche. 2019. Association of age and gender with anxiety disorders in older adults: A systematic review and meta-analysis. *International Journal of Geriatric Psychiatry* 34: 397–407. [CrossRef] [PubMed]

Handing, Elizabeth P., Carolin Strobl, Yuqin Jiao, Leilani Feliciano, and Stephen Aichele. 2022. Predictors of depression among middle-aged and older men and women in Europe: A machine learning approach. *The Lancet Regional Health–Europe* 18: 100391. [CrossRef] [PubMed]

Hughes, Mary Elizabeth, Linda J. Waite, Louise C. Hawkley, and John T. Cacioppo. 2004. A short scale for measuring loneliness in large surveys: Results from two population-based studies. *Research on Aging* 26: 655–72. [CrossRef] [PubMed]

Infurna, Frank J., Nutifafa E. Y. Dey, Tita Gonzalez Avilés, Kevin J. Grimm, Margie E. Lachman, and Denis Gerstorf. 2024. *Loneliness in Midlife: Historical Increases and Elevated Levels in the United States Compared with Europe*. Washington, DC: American Psychologist. [CrossRef]

Javaid, Syed Fahad, Ibrahim Jawad Hashim, Muhammad Jawad Hashim, Emmanuel Stip, Mohammed Abdul Samad, and Alia Al Ahbabi. 2023. Epidemiology of anxiety disorders: Global burden and sociodemographic associations. *Middle East Current Psychiatry* 30: 44. [CrossRef]

Kessler, Ronald C., Matthias Angermeyer, James C. Anthony, R. O. N. De Graaf, Koen Demyttenaere, Isabelle Gasquet, Giovanni De Girolamo, Semyon Gluzman, Oye Gureje, Josep Maria Haro, and et al. 2007. Lifetime prevalence and age-of-onset distributions of mental disorders in the World Health Organization's World Mental Health Survey Initiative. *World Psychiatry* 6: 168.

Lancet Global Health. 2020. Mental health matters. *The Lancet Global Health* 8: e1352. [CrossRef]

Li, Liming, Ludovico Carrino, Erica Reinhard, and Mauricio Avendano. 2024a. Has the UK Campaign to End Loneliness reduced loneliness and improved mental health in older age? A difference-in-differences design. *The American Journal of Geriatric Psychiatry* 32: 358–72. [CrossRef]

Li, Yutong, Yipeng Song, Jie Sui, Russell Greiner, Xin-min Li, Andrew J. Greenshaw, Yang S. Liu, and Bo Cao. 2024b. Prospective prediction of anxiety onset in the Canadian longitudinal study on aging (CLSA): A machine learning study. *Journal of Affective Disorders* 357: 148–55. [CrossRef]

Lijster, Jasmijn M. De, Bram Dierckx, Elisabeth M. W. J. Utens, Frank C. Verhulst, Carola Zieldorff, Gwen C. Dieleman, and Jeroen S. Legerstee. 2017. The age of onset of anxiety disorders: A meta-analysis. *The Canadian Journal of Psychiatry* 62: 237–46. [CrossRef]

Lim, Michelle H., Thomas L. Rodebaugh, Michael J. Zyphur, and John F. M. Gleeson. 2016. Loneliness over time: The crucial role of social anxiety. *Journal of Abnormal Psychology* 125: 620–30. [CrossRef]

Litwin, Howard, and Kimberly J. Stoeckel. 2015. Social network, activity participation, and cognition: A complex relationship. *Research on Aging* 38: 76–97. [CrossRef] [PubMed]

Liu, Yuqi, Zhuolin Pan, Ye Liu, and Zhigang Li. 2023. Can living in an age-friendly neighbourhood protect older adults' mental health against functional decline in China? *Landscape and Urban Planning* 240: 104897. [CrossRef]

Nagelkerke, Nico J. D. 1991. A note on a general definition of the coefficient of determination. *Biometrika* 78: 691–92. [CrossRef]

National Academies of Sciences Engineering and Medicine, Health and Medicine Division, Board on Health Sciences Policy Division of Behavioral and Social Sciences and Education, Board on Behavioral Cognitive and Sensory Sciences, and Committee on the Health and Medical Dimensions of Social Isolation and Loneliness in Older Adults. 2020. *Social Isolation and Loneliness in Older Adults: Opportunities for the Health Care System*. Washington, DC: National Academies Press.

Novak, Sara. 2024. Americans are Lonelier than Europeans in Middle Age. *Scientific American*. Available online: https://www.scientificamerican.com/article/americans-are-lonelier-than-europeans-in-middle-age/ (accessed on 15 June 2024).

Puterman, Eli, Jordan Weiss, Benjamin A. Hives, Alison Gemmill, Deborah Karasek, Wendy Berry Mendes, and David H. Rehkopf. 2020. Predicting mortality from 57 economic, behavioral, social, and psychological factors. *Proceedings of the National Academy of Sciences* 117: 16273–82. [CrossRef]

R Core Team. 2024. *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing. Available online: https://www.r-project.org/ (accessed on 15 June 2024).

Ridley, Matthew, Gautam Rao, Frank Schilbach, and Vikram Patel. 2020. Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science* 370: eaay0214. [CrossRef]

Santabárbara, Javier, Darren M. Lipnicki, Beatriz Olaya, Beatriz Villagrasa, Juan Bueno-Notivol, Lucia Nuez, Raúl López-Antón, and Patricia Gracia-García. 2020. Does anxiety increase the risk of all-cause dementia? An updated meta-analysis of prospective cohort studies. *Journal of Clinical Medicine* 9: 1791. [CrossRef]

Schneider, Silke L. 2013. The international standard classification of education 2011. In *Class and Stratification Analysis*. Bingley: Emerald Group Publishing Limited, vol. 30, pp. 365–79.

SHARE-ERIC. 2024. *Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 5*. Release Version: 9.0.0. Berlin: SHARE-ERIC. [CrossRef]

Smith, Kevin, Aaron Weinschenk, and Costas Panagopoulos. 2024. On pins and needles: Anxiety, politics and the 2020 US Presidential election. *Journal of Elections, Public Opinion and Parties* 34: 409–26. [CrossRef]

Smith, Ronald, Viviana Wuthrich, Carly Johnco, and Jessica Belcher. 2021. Effect of group cognitive behavioural therapy on loneliness in a community sample of older adults: A secondary analysis of a randomized controlled trial. *Clinical Gerontologist* 44: 439–49. [CrossRef]

Steen, Olivier D., Anil P. S. Ori, Klaas J. Wardenaar, and Hanna M. Van Loo. 2022. Loneliness associates strongly with anxiety and depression during the COVID pandemic, especially in men and younger adults. *Nature Scientific Reports* 12: 9517. [CrossRef]

Strobl, Carolin, Anne-Laure Boulesteix, Achim Zeileis, and Torsten Hothorn. 2007. Bias in random forest variable importance measures: Illustrations, sources and a solution. *BMC Bioinformatics* 8: 25. [CrossRef]

Strobl, Carolin, James Malley, and Gerhard Tutz. 2009. An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological Methods* 14: 323. [CrossRef] [PubMed]

Van Buuren, Stef, and Karin Groothuis-Oudshoorn. 2011. MICE: Multivariate imputation by chained equations in R. *Journal of Statistical Software* 45: 1–67. [CrossRef]

Vink, Dagmar, Marja J. Aartsen, and Robert A. Schoevers. 2008. Risk factors for anxiety and depression in the elderly: A review. *Journal of Affective Disorders* 106: 29–44. [CrossRef] [PubMed]

Volkert, Jana, Holger Schulz, Martin Härter, Olga Wlodarczyk, and Sylke Andreas. 2013. The prevalence of mental disorders in older people in Western countries–a meta-analysis. *Ageing Research Reviews* 12: 339–53. [CrossRef]

Weisberg, Risa B. 2009. Overview of generalized anxiety disorder: Epidemiology, presentation, and course. *Journal of Clinical Psychiatry* 70 S2: 4–9. [CrossRef] [PubMed]

Weisberg, Risa B., Courtney Beard, Ethan Moitra, Ingrid Dyck, and Martin B. Keller. 2014. Adequacy of treatment received by primary care patients with anxiety disorders. *Depression and Anxiety* 31: 443–50. [CrossRef]

Witlox, Maartje, Nadia Garnefski, Vivian Kraaij, Meropi Simou, Elise Dusseldorp, Ernst Bohlmeijer, and Philip Spinhoven. 2021. Prevalence of anxiety disorders and subthreshold anxiety throughout later life: Systematic review and meta-analysis. *Psychology and Aging* 36: 268. [CrossRef]

Wolitzky-Taylor, Kate B., Natalie Castriotta, Eric J. Lenze, Melinda A. Stanley, and Michelle G. Craske. 2010. Anxiety disorders in older adults: A comprehensive review. *Depression and Anxiety* 27: 190–211. [CrossRef]

World Health Organization. 2024. Mental Health of Older Adults [Fact Sheet]. Available online: https://www.who.int/news-room/fact-sheets/detail/mental-health-of-older-adults#:~:text=Some%20older%20adults%20are%20at,to%20quality%20support%20and%20services (accessed on 15 June 2024).