COGNITIVE DECLINE AMONG OLDER ADULTS IN EUROPE: AN ANALYSIS OF EASYSHARE DATA

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Abstract. Today, the progressive aging of the world population represents a crucial issue, with significant consequences implications for public health. Among the most relevant concerns related to third age, cognitive decline and depression have been found to be closely interconnected, both influenced by a wide range of socio-demographic, biological and behavioral factors. Using the easySHARE dataset—a reduced version of the SHARE (Survey of Health, Ageing and Retirement in Europe) study — these phenomena were analyzed by focusing on EU residents aged 64 years and older, as of 2022.
The analyses employed statistical methods, including linear regression models, with the aim of identifying variables strongly associated with cognitive decline. The findings indicate that factors such as educational attainment, self-perceived health, and regular physical activity significantly contribute to reducing cognitive risks. Other factors, such as the cohabitation with a partner or maintaining a healthy diet, also demonstrate protective effects on cognitive well-being.
Notably, depression emerged as a relevant predictor of cognitive decline, highlighting the potential value of psychological support in treating depression as a means to also slow the cognitive decay.
This highlights the urgent need for policies and interventions aimed at promoting active and "successful" aging, ultimately contributing to an improved quality of life for older adults in Europe.

1. Introduction

Aging represents an inevitable stage of life, marked by physiological, cognitive, and social changes. In recent decades, the sharp rise in the elderly population has raised questions about its impact on public health. Projections suggest that by 2050, the global proportion of people over the age of 60 will double, rising from 11% in 2006 to 22% (Galluzzo *et al.*, 2012). This demographic shift is expected to have significant implications across healthcare, economic systems, and society, highlighting the importance of understanding the factors that affect quality of life in later years.

One of the key aspects of healthy aging is the preservation of cognitive abilities. Concepts like successful aging and active aging have gained increasing attention, in recent years (Estebari *et al.*, 2020; Kanungo, 1975). These ideas refer to a condition in which individuals maintain their independence, psychological well-being, and cognitive function, while avoiding or delaying cognitive decline. However, aging is not a uniform process: there are considerable differences between individuals, shaped by genetic, environmental, and lifestyle factors.

Cognitive decline represents one of the major challenges of aging, as cognitive functions—like memory, language, attention, and information processing—are essential for maintaining daily functioning and quality of life. Losing these capacities can lead to debilitating conditions, including dementia, that compromise individual autonomy and increase demands on families and healthcare systems. Identifying both risk and protective factors for cognitive deterioration is therefore critical for the development of effective preventive strategies.

Previous studies, cited below, have highlighted several key variables that significantly influence cognitive function in older adults, underscoring the multifactorial nature of cognitive health:

Educational and social factors: Education plays a crucial role in the development and preservation of cognitive abilities. Evidence indicates that individuals with higher levels of education perform better on cognitive assessments and show a reduced risk of cognitive decline compared to those with lower educational backgrounds (Lövdén *et al.*, 2020; Van Hooren *et al.*, 2007; Yaffe *et al.*, 2009). Engagement in social and volunteer activities also has been associated with a protective effect (Park *et al.*, 2019).

Lifestyle and physical health: Regular physical activity is positively associated with better cognitive performance, while smoking constitutes a notable risk factor for cognitive deterioration (Brewster *et al.*, 2014; Falk *et al.*, 2019). The established link between physical and cognitive health suggests that integrated interventions may promote healthier aging.

Psychological and clinical conditions: Several studies (Champaneria and McArthur, 2022; Schuitevoerder *et al.*, 2013) have identified that disorders such as post-traumatic stress disorder (PTSD) may compromise cognitive function in older adults, increasing susceptibility to memory deficits and decision-making difficulties.

To provide additional support for these findings and to explore how these factors interact in shaping individual cognitive path, the present study draws on data from the 2022 wave of the SHARE dataset (Survey of Health, Ageing and Retirement in Europe). Through the application of regression models, the study identifies the most significant predictors of cognitive decline, with the aim of delineating the characteristics and behaviors associated with successful aging among older adults in the European Union.

This study focuses on the following research questions:

RQ1. What are the main factors that influence cognitive performance in older adults?

RQ2. How do sociodemographic characteristics, lifestyle behaviors, and health conditions impact cognitive functioning in the elderly?

Understanding these mechanisms may contribute to the development of evidence-based public policies and targeted interventions aimed at improving mental health and quality of life in aging populations.

2. Data and Methods

2.1. Data

The present analysis is based on data from the easySHARE dataset, which is a simplified version derived from the SHARE database[1]. The sample includes individuals aged over 64 years who participated in wave 9 (year 2022), resulting in a total of 33,436 respondents. The variables included into the regression model cover multiple domains:

- **Demographic factors**: gender, citizenship, and educational attainment.
- **Household composition**: living with a partner in the same household.
- **Social support**: geographic proximity of children and social support.
- **Health status and health-related behaviours**: self-perceived health, the EURO-D depression scale, body mass index, smoking habits, and engagement in vigorous physical activity or sports.
- **Functional limitations**: cognitive performance indicators.

2.2. Methods

Following the selection of the sample, preliminary descriptive analyses were conducted to assess the distribution of the variables of interest within the study population, to explore their characteristics and potential correlations among them.

To evaluate mental health, the *'eurod'* variable is employed, an index measuring depressive symptoms based on the questions included in the mental health module (mh002_ to mh017_). This twelve items assessing various symptoms: depressed mood, pessimism, suicidal thoughts, feelings of guilt, hypersomnia, anhedonia,

[1] https://share-eric.eu/

irritability, appetite disturbance, fatigue, concentration difficulties, joy, and sadness. The index ranges from 0 (absence of depressive symptoms) to 12 (high levels of depression). This variable was recoded into four categorical levels:

- A (low): scores between 0 and 3
- B (medium-low): scores between 4 and 6
- C (medium-high): scores between 7 and 9
- D (high): scores between 10 and 12

Regarding the cognitive decline, due to the absence of a direct variable in the dataset available, an index was constructed based on four items derived from the module on current cognitive functioning among respondents.

- recall_1: Number of words recalled in the first trial of the word recall task, with scores ranging from 0 to 10.
- recall_2: Number of words recalled in the delayed word recall task. Scores range from 0 to 10.
- orienti: Testing the ability to identify the current year, month, calendar date, and day of the week. Ranges from 0 (poor temporal orientation) to 4.
- numeracy_2: Outcome of a numerical task involving basic subtraction. Score ranges from 0 (low performance) to 5 (high performance).

After rescaling *orienti* and *numeracy_2* to a standardized 0–10 scale, the four variables were aggregated to construct a composite index—referred to as *'cognitive'*— which reflects overall cognitive performance in wave 9 (2022), with a total score ranging from 0 to 40.

The statistical approach employed is a linear regression model incorporating categorical independent variables (1). This is an extension of linear regression that allows for the inclusion of qualitative (or categorical) predictors, and in this context, it is utilized to model cognitive decline as a function of several categorical factors:

$$Y = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \cdots + \epsilon, \quad (1)$$

where:

- Y: denotes the *cognitive* index, used as the dependent variable.
- D_1, D_2, …: represent categorical predictors included as dummy variables: gender, educational level, cohabitation, residential proximity of children, external

assistance, perceived health status, BMI, physical activity, smoking habits, migration background, and level of depressive symptoms.

- β_0 : intercept.
- β_1, β_2, …: are the regression coefficients that show the estimated effect of each predictor on the dependent variable.
- ϵ: the residual term capturing unexplained variance

3. Results

3.1. Data Pre-processing

The dataset was checked for missing data, identification of outliers, multicollinearity, and model selection procedures.

Regarding missing data, 1,807 observations were excluded due to the presence of missing values in at least one of the variables included in the model.

To identify influential observations potentially affecting the robustness of the regression estimates, Cook's Distance was employed. Observations flagged as outliers based on this measure were subsequently removed from the analysis.

Multicollinearity was evaluated using Tolerance (TOL) and the Variance Inflation Factor (VIF). A VIF value exceeding 5 indicates problematic multicollinearity, while a low TOL value (approaching 0) similarly suggests high inter-variable correlation.

Finally, to optimize model specification and limit overfitting, a stepwise selection procedure with both forward and backward elimination ("stepwise both") was applied. This approach ensures the retention of statistically relevant predictors only.

Figure 1 – *Cook's distance.*

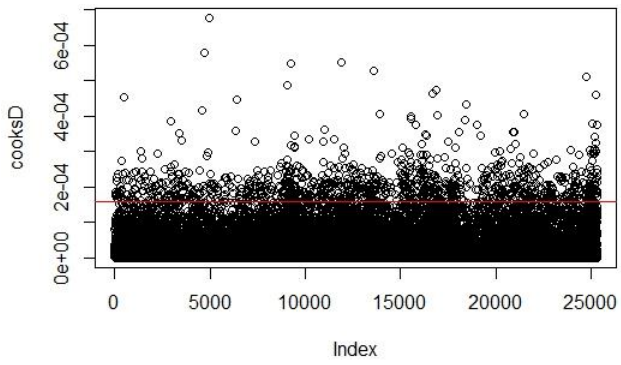

*Figure notes: displays Cook's Distance (*cookD*) plotted against the observation index.*

The majority of data points fall just below the threshold line, represented by the red horizontal line, indicating that most observations are not particularly influential on the model estimates. While a few points deviate slightly from the central distribution, the overall spread remains constrained, suggesting a generally stable model fit.

Figure 2 – *Q-Q Residuals.*

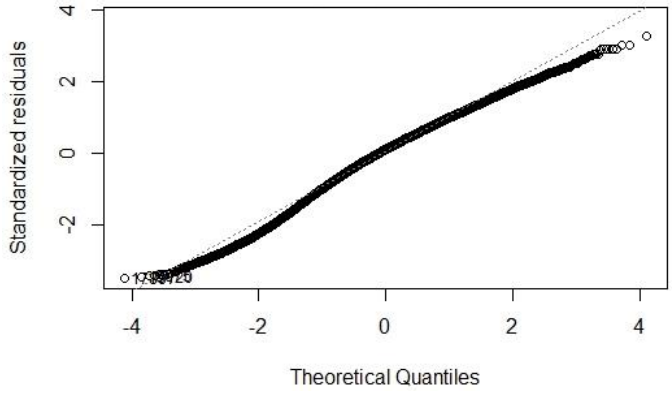

Figure notes: shows the Q-Q plot of the standardized residuals for the regression model.

Most points fall close to the diagonal line, corresponding to the theoretical normal distribution, suggesting that the residuals approximate normality overall. Minor deviations are observed at both tails of the distribution, indicating potential departures from normality at the extremes. However, given the limited extent of these deviations and the substantial sample size, their impact on the validity of model-based inferences is expected to be minimal.

Table 1 – Variance Inflation Factor (VIF) and Tolerance (TOL)

Independent variables	VIF	TOL
Gender	1,144	0,874
Educational Attainment	1,123	0,890
Cohabitation	1,156	0,865
Proximity of children's residence	1.035	0,966
External assistance	1,083	0,923
Self-perceived health	1,338	0,747
Body Mass Index	1,054	0,948
Physical activity	1.142	0,876
Smoking habits	1.016	0,984
Migrant	1,008	0,992
Depression level	1,239	0,807

Table notes: show VIF and TOL values for the set of independent variables

All VIF values are very low (from 1.008 to 1.338), remaining well below the conventional cut-off value of 5, indicating an absence of substantial multicollinearity. Similarly, TOL values are consistently high (between 0.747 and 0.992), above the commonly used threshold of 0.2. These results suggest that each predictor contributes for a meaningful portion of its variance and retains a sufficient degree of independence from the others.

3.2. Linear Regression Model

The regression output reveals that the majority of predictors have statistically significant effects on the dependent variable ($p < 0.001$).

Gender emerges as a significant factor: being female is associated with a 1.0657-point increase in cognitive performance, relative to the male reference category. This suggests a modest but consistent cognitive advantage for women in the sample.

The categorical variable which represent levels of education, demonstrates a clear positive gradient. Relative to individuals with no formal education, those with tertiary education (second cycle) show an increase of 8.0441 units in the cognitive index. These findings underscore the critical role of educational background as a protective factor against age-related cognitive decline.

Table 2 – *LINEAR REGRESSION MODEL – Categorical Independent Variables*.

Independent variables	Estimate	Std. Error	t-value	Pr(>|t|)	
Intercept	22,387	0,412	54,283	< 2e-16	***
Gender					
female	1,066	0,059	18,034	< 2e-16	***
Educational Attainment					
primary education	2,193	0,219	10,032	< 2e-16	***
lower secondary education	4,262	0,216	19,695	< 2e-16	***
upper secondary education	5,821	0,212	27,522	< 2e-16	***
post-secondary education	6,545	0,246	26,641	< 2e-16	***
first stage of tertiary education	7,335	0,216	34,015	< 2e-16	***
second stage of tertiary education	8,044	0,376	21,385	< 2e-16	***
still in school	-0,473	2,525	-0,187	< 2e-16	***
other	6,087	0,864	7,048	< 2e-16	***
Cohabitation					
living without a spouse/partner	-0,748	0,062	-12,047	< 2e-16	***
Proximity of children's residence					
no	0,514	0,057	9,054	< 2e-16	***
External assistance					
no	0,127	0,067	1,888	0,05902	.
Self-perceived health					
very good	0,095	0,153	0,616	0,53759	
good	-0,863	0,142	-6,074	1,26e-09	***
fair	-1,890	0,147	-12,893	< 2e-16	***
poor	-3,254	0,172	-18,925	< 2e-16	***
Body Mass Index					
normal	0,861	0,315	2,732	0,00631	**
overweight	1,033	0,315	3,280	0,00104	**
obese	1,356	0,317	4,282	1,86e-05	***
Physical activity					
once a week	-0,251	0,091	-2,748	0,00600	**
one to three times a month	-0,235	0,098	-2,400	0,01641	*
hardly ever, or never	-1,038	0,069	-15,012	< 2e-16	***
Smoking habits					
no	-0,570	0,089	-6,434	1,27e-10	***
Migrant					
yes	0,035	0,215	0,161	0,87189	
Depression level					
medium-low	-0,652	0,071	-9,144	< 2e-16	***
medium-high	-2,341	0,134	-17,497	< 2e-16	***
high	-5,924	0,519	-11,406	< 2e-16	***

*Signif. Codes * p<0,01; ** p< 0,05; *** p<0,001*

Table notes: regression model results

Living alone is associated with a statistically significant decrease of 0.7478 units in the cognitive index, indicating that cohabitation may act as a protective factor for cognitive functioning in older adults.

The Body Mass Index (BMI) has a positive association with cognitive performance, with higher BMI categories linked to higher cognitive scores. These results suggest that lower BMI values— that might indicate undernutrition or frailty in older populations —may be associated with accelerated cognitive decline.

Regarding depression, the negative and significant coefficients confirm its effect on cognitive health. In particular, individuals classified within the highest depression category exhibit a reduction of approximately 6 points in the cognitive index, underscoring the substantial cognitive burden associated with severe depressive symptoms.

Self-perceived health and physical activity levels demonstrate a progressively negative effect, indicating that declines in subjective health status and reductions in physical activity are associated with a deterioration in cognitive performance.

Interestingly, the absence of sons or daughters live within one kilometre of the respondent and the lack of external support from individuals outside the household are associated with improved cognitive outcomes. This may reflect a greater level of autonomy and preserved cognitive functioning among individuals who do not require external assistance.

After the application of stepwise model selection, MIGRANT was the only one excluded, as it did not significantly affect R-squared or adjusted R-squared values.

4. Conclusions

Cognitive decline has effects on the everyday functioning of older adults. However, the severity of cognitive deterioration exhibits considerable variability from person to person and is shaped by a multitude of determinants.

This study contributes to the understanding of this heterogeneity by identifying key determinants associated with slower cognitive deterioration, focusing on sociodemographic characteristics, health status, and behavioral factors.

Educational attainment emerged as a crucial factor in maintaining cognitive functioning. Individuals with higher levels of education consistently achieved superior cognitive scores. This association is likely mediated by better life conditions and enhanced socioeconomic status (Dekhtyar *et al*., 2015).

This evidence highlights the potential long-term benefits of educational investments during childhood and adolescence, as it could help reduce the personal and social costs of cognitive decline in old age. Furthermore, these findings advocate

for the implementation of public policies that promoting access to education and encouraging lifelong learning, even in adulthood.

Perceived health status also emerged as a key factor of cognitive functioning. A negative perception of one's own health is strongly correlated with cognitive deterioration, underscoring the importance of interventions that enhance subjective well-being. This includes access to comprehensive psychological support services and adequate healthcare infrastructure. Focus on mental health, especially through the prevention and management of depressive disorders, is fundamental, given their robust association with cognitive decline, as supported by previous research (Halfin, 2007; Reynolds *et al*., 2012). The results also identify social isolation as a major risk factor for cognitive impairment.

Regular physical activity has emerged as a robust predictor of cognitive health. Older individuals who engage in consistent exercise tend to display superior cognitive performance, a finding consistent with the neurobiological literature that highlights the role of physical activity in enhancing neuroplasticity and mitigating the risk of neurodegenerative pathologies.

Overall, this study contributes to the literature by integrating multiple life-course determinants of cognitive aging within the same analytical framework. However, due to the cross-sectional nature of the data, only association can be identified, while causality cannot be determined. Additionally, the self-reported measures may be subject to reporting bias. Future research would benefit from longitudinal approaches to better capture the mechanisms underlying cognitive decline.

In the context of accelerated demographic aging across Europe, the identification of key determinants of mental and cognitive health in late adulthood represents not only a scientific imperative but also a social priority. Promoting the cognitive and emotional well-being of older adults constitutes a strategic investment in the future of society, shifting the narrative of aging from a burden to an opportunity, to recognize the value and potential of an increasingly long-lived population.

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