The Impact of Big Five Personality Traits on Older Europeans' Physical Health

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ABSTRACT

Investigating the role of Big Five personality traits in relation to various health outcomes has been extensively studied. The impact of "Big Five" on physical health is here explored for older Europeans with a focus on examining age groups differences. The study sample included 378,500 respondents derived from the seventh data wave of Survey of Health, Aging and Retirement in Europe (SHARE). The physical health status of older Europeans was estimated by constructing an index considering the combined effect of well-established health indicators such as the number of chronic diseases, mobility limitations, limitations with basic and instrumental activities of daily living, and self-perceived health. This index was used for an overall physical health assessment, for which the higher the score for an individual, the worst health level. Then, through a dichotomization process applied to the retrieved Principal Component Analysis scores, a two-group discrimination (good or bad health status) of SHARE participants was obtained as regards their physical health condition, allowing for further constructing logistic regression models to assess the predictive significance of "Big Five" and their protective role for physical health. Results showed that neuroticism was the most significant predictor of physical health for all age groups under consideration, while extraversion, agreeableness and openness were not found to significantly affect the self-reported physical health levels of midlife adults aged 50 up to 64. Older adults aged 65 up to 79 were more prone to openness, whereas the oldest old individuals aged 80 up to 105 were mainly affected by openness and conscientiousness.

1. INTRODUCTION

The Big Five personality traits model is considered by many modern psychologists as the most appropriate one to describe and estimate individual personality behaviors and variations [1]. It was prevailed and established through the years by researchers who supported this theory with the selection of five core personality dimensions including extraversion, agreeableness, openness to experience, conscientiousness, and neuroticism [2]. Each of these factors ranges between two extreme conditions describing the state that an individual could be found. Extraversion describes the sociability, assertiveness, and emotional expressiveness. Individuals with high extraversion rates enjoy meeting new people and make easily new friends compared to those having low rates, being introverted and thus, preferring solitude. Agreeableness includes the elements of trust, kindness, and affection. As a result, those scoring high in this dimension show special interest to other people, feel empathy and concern, and like contributing to their happiness. Openness to experience refers to the imagination and willingness to learn new things. People with high openness rates tend to be very creative and open minded in facing new challenges, whereas those low in this personality trait do not enjoy trying new things and resist new ideas. Further, individuals scoring high in conscientiousness are characterized by thoughtfulness, carefulness and organizational skills allowing them to be mindful of details and deadlines. Finally, neuroticism is followed by sadness and emotional instability. People that score high on this trait usually experience a lot of stress, irritability and worries about different things in contrast to those being more relaxed and emotionally stable.

1.1. Association between Big Five Traits and Health

Investigating the role of Big Five personality traits in relation to various health outcomes is of major importance. Past research findings support that neuroticism is significantly positively correlated with psychotic experiences, whereas the remaining attributes significantly move in the opposite direction [3]. Jerram and Coleman [4] found that neuroticism is associated with several reported medical problems, negative self-perceived health status and the frequency of patients' consulting in general practice. The authors' findings also support that extraversion is related to positive health behaviors and openness to experience, while agreeableness is associated with positive health perceptions. Further, Goodwin and Friedman [5] showed that conscientiousness is associated with significantly reduced likelihood of a wide range of mental and physical disorders among the adult population, while the opposite holds as regards neuroticism. Finally, Löckenhoff *et al.* [6] provided evidence that agreeableness and openness are associated with better subjective physical and mental health, extraversion and conscientiousness were found to be positively associated with both physical and mental health, whereas neuroticism was negatively associated.

Furthermore, recent medical studies have shown that pharmacological adherence in old ages is associated with Big Five personality traits. Low adherence in elderly is negatively associated with the neuroticism factor, whereas high adherence is positively related to agreeableness and conscientiousness dimensions [7]. For patients suffering from cardiovascular diseases, the trait of conscientiousness acts positively in the improvement of medication adherence [8]. In addition, past research epidemiological studies revealed the existence of mediating factors between personality traits and health-related quality of life for people suffering from chronic diseases. For instance, the effect of extraversion and conscientiousness on the mental part of health-related quality of life was mediated by self-efficacy, whereas the effect of agreeableness and conscientiousness was partly mediated by adherence. Lastly, neuroticism seemed to have a direct effect on both physical and mental parts of health-related quality of life [9], whereas other authors correlated neuroticism with depressive disorders suggesting the further investigation of predictors that could mediate the relationship between personality aspects and emotional disorders [10]. Moreover, several authors have associated neuroticism with higher rates of chronic diseases and higher risk of developing an illness [11, 12], while other studies revealed that higher extraversion, conscientiousness and openness, lower neuroticism, but not agreeableness, are related to higher physical functioning [13].

1.2. Association between Big Five Traits and Age

The role of Big Five personality traits has also been studied in relation to the age parameter. Kersting [14] studied trends in the Big Five characteristics across the lifespan including adults aged 21 - 60. Donnellan and Lucas [15] included individuals aged from 16 to 84 years old in their study and found that extraversion and openness are negatively associated with age, whereas a positive association was found as regards agreeableness. Middle-aged participants scored the highest levels of conscientiousness, while neuroticism was slightly negatively associated with age as regards the British population and slightly positively associated as regards the German population. Similarly, Kawamoto *et al.* [16] found that agreeableness and conscientiousness are positively correlated to age, while Baek *et al.* [17] concluded that low scores on neuroticism and high scores on the rest characteristics of the Big Five Model were significantly related to factors associated with successful aging. Recently, Kang [18] revealed that personality traits relate differently to self-rated health at different ages for people residing in United Kingdom, and separated participants into three groups, that is aged <40 (young people), aged >39 and <60 (middle-aged individuals), and aged >59 (referred as older people).

1.3. The Present Study

Based on the aforementioned findings, it can be seen that researchers have already provided evidence for the existence of age-related changes in the "Big Five" across the life span and outlined a discernible relationship between personality traits and better health, physical and mental as well. Further, according to current research (see Israel *et al.* [19]), personality traits remain stable over many years and have far-ranging effects on health, while there is an apparent relationship between the trait of conscientiousness and better health. Specifically, the latter study suggests that conscientious young adults enjoy better health as they age, and highlights that being conscientious appears to be the best bet for good health among Big Five traits, with individuals low in conscientiousness being more likely to develop multiple health problems. It is thus undoubtable that personality may be a key risk factor in preventive health care. However, to date, many questions remain about how personality psychology should be translated to allow personalizing preventive health care and medicine for patients, there is limited community level data globally toward this direction, and no comprehensive summary of the current data on this issue has until now been made widely available. In fact, at present most of the relevant studies are either cross-sectional, the longitudinal ones have few follow-up times and some of them do not adopt by design methods for representative sample recruiting. There are therefore many benefits for researchers and practitioners in the field of mental health and psychosocial support to utilize published epidemiological and psycho-socioeconomic data based on representative sampling (such as the data of the "Survey of Health, Ageing and Retirement in Europe—SHARE") in order to achieve a general understanding of personality's effect in preventive health care, design an integrated health preventive care system, and thereby implement effective management strategies.

In light of this, and mindful of the increasing research interest worldwide for the age-related differences in personality traits and their association with better health, the goal of this study is to examine the role of Big Five personality traits in relation to various health factors in a holistic manner, that is estimating how personality traits impact patients' attitudes and behaviors vis-à-vis their physical health. For this purpose, SHARE data were retrieved and analyzed in this paper. In this way, we intend to highlight that the best health care system is the one that "treats the person as a whole". Knowing "who the patient is" in terms of personality traits along with considering "what a patient has among risks" for chronic age-related diseases, constitutes a holistic approach to provide effective preventive health care. It is worth noting here that, to the best of our knowledge, the impact of Big Five personality characteristics on physical health has not been previously studied in such a holistic manner, and no previous research has focused on age-related differences among the Big Five personal traits for Europeans aged 50 or higher. For this scope, in this paper, several health indicators measuring respondents' physical health have been taken into consideration for the analysis purposes, and one component was extracted measuring the physical health status of participants as a whole, while age-related differences among older Europeans were further examined.

1.4. Research Hypotheses

The first hypothesis of the present study is that Big Five personality traits significantly predict the "new" constructed physical health index following the trends and findings already been formulated. The second hypothesis is that the footprint of the Big Five personal traits on the physical health index differentiates among three age groups covering middle life to the across span. For this purpose, based on the definition of an older or elderly person given by the World Health Organisation (WHO), participants were put into three age groups ranging from middle life (50 - 64 years), older ages (65 - 79 years) and oldest old individuals (80 - 105 years), and comparisons were made.

The rest of the paper is organized as follows. In Section 2, the research study design (*i.e.*, data source, methodological considerations and employed procedures) and the statistical analysis framework are provided. In Section 3, results are presented in detail to illustrate the implementation of the methodological framework in practice, and to unfold its capabilities. Finally, in Section 4, research findings are discussed, and some concluding remarks are made. Further, study's limitations and strengths, implications for practice, and suggestions for future research are given.

2. METHOD

2.1. Transparency and Openness

We used data from the 7th wave of SHARE. Data collection of SHARE Wave 7 started in March 2017 and ended on 31 October 2017. As this is a secondary data analysis, we cannot make the data available, but SHARE data are distributed by SHARE-ERIC (Survey of Health, Ageing and Retirement in Europe—European Research Infrastructure Consortium) after an individual user's registration through the SHARE Research Data Center (https://share-eric.eu/data/data-access). For materials, questionnaires, interview codebook, and SHARE Wave 7 Methodology, the interested reader may refer to Bergmann *et al.* [20], Börsch-Supan *et al.* [21], and Börsch-Supan [22]. The study design, hypotheses and the analytic plan were not preregistered. Data were analyzed using IBM SPSS Statistics (v. 20) and the analytic code for statistical analyses is provided (see Acknowledgments section for further details). In the following, we report the sampling frame, imputation method, data preparations, and measures that were used for this study.

2.2. Procedure and Participants

For the analysis purposes of the present study, micro-data from SHARE were used. SHARE is a database collecting elements for European residents aged 50 or higher regarding their health, demographic, economic and social aspects of their life [22]. The initial research sample included 378,500 observations, deriving from the seventh wave of SHARE, held in 2017 and thereafter it was divided into five imputed datasets, including 75,700 individuals each, aged over 50 years and residing in 27 European countries. A hot deck imputation method was implemented for handling missing data which are often a problem in large-scale surveys (arising as unit non-response or/and item non-response). Hot deck is a widely popular imputation method among survey practitioners suitably applied to any kind of variables included in a dataset having insignificant levels of missing values, usually much less than 5%. According to the method, non-observation (missing values) for one or more variables for a non-respondent (the recipient) are replaced with the observed values from a respondent (the donor) that is "similar" to the recipient based on some distance metric [23]. As the implementation of the procedure generates additional variability, the method provides five imputations of missing values, being constructed through five independent recurrences of the hot-deck imputation technique. It is worth noting that, users of imputed datasets should analyze data considering wholly five iterations of variables otherwise results may be imprecise [24].

2.3. Measures

2.3.1 Health-Related Indicators

The physical health status of participants is here measured considering a combination of variables such as the number of chronic diseases, the number of mobility limitations, the number of limitations with activities of daily living (ADL), the number of limitations with instrumental activities of daily living

(IADL), and self-perceived health (SPH). The number of chronic diseases and mobility limitations are measured in a discrete form. In particular, the number of chronic diseases is the result of aggregating responses to the battery of questions as to whether the person interviewed has been diagnosed with any of all possible chronic diseases included in the questionnaire. As for mobility limitations, this is measured by an aggregate total score of mobility, arm functioning and fine motor limitations reported. Further, ADL and IADL are used to assess the limitations in common activities and self-care tasks in everyday life, measuring the capability and the help received or needed in relation to six basic activities as regards ADL and nine instrumental activities of daily living as regards IADL respectively. Basic ADL includes the standard daily activities and tasks which are necessary for self-maintenance such as dressing (including putting on shoes and socks), walking across a room, bathing and showering, eating (such as cutting up your food), getting in and out of bed, and using the toilet (including getting up or down). IADL refers to more complex responsibilities and higher-level functions with a greater requirement of personal autonomy and interaction with the environment, such as using a map to figure out how to get around in a place, preparing a hot meal, shopping for groceries, making telephone calls, taking medications, doing work around the house or garden, managing money (such as paying bills and keeping track of expenses). The lowest score is 0 (maximal autonomy) and the maximum score is 6 and 9 (full limitations in activities autonomy) for ADL and IADL, respectively, with higher values indicating worsening health status because of physical, mental, emotional, or/and memory problems. SPH expresses subjective assessment by the respondent of his/her health. It is measured via a single-item question which includes a rating of health status from excellent (1) to poor (5) on a 5-point scale, and the higher the indicator value, the worse health perception. It is worth noting here that, according to a European study's findings, ADL, IADL, chronic diseases and depression are the four objective health conditions that most significantly influence SPH and define the level of subjective health that a respondent will record for age groups of 50 - 64 and 65 - 79. Moreover, SPH is influenced by chronic diseases till the age of 65, and by IADL limitations to the next age group including 65 - 79 years. Further, ADL limitations have been already found to play an important role for women in middle life (*i.e.*, 50 - 64 years) that do not suffer from chronic conditions. However, even if these findings interplaying SPH are illuminating, none of the previous four indicators itself can totally substitute the individual perception of health as it is expressed through the SPH factor [25].

2.3.2. Physical Health Metric

In this paper, Principal Component Analysis (PCA) is adopted considering the aforementioned subjective (SPH) and objective (chronic diseases, mobility limitations, ADL, IADL) health-related measures in order to obtain a single factor/component representing the level of individual physical health status.

PCA is a multivariate statistical technique [26, 27] typically used for the dimensional reduction of multivariate data whilst maintaining as much of the data information as possible. PCA enables capturing the original variability with the use of less variables. The used criterion is the maximization of the information variance, with the highest variance of the transformed data attributed to the first component, the second highest variance to the second component and so on, while principal components are "new" independent variables that are constructed as linear combinations or mixtures of the initial variables.

Many authors use interchangeably either PCA or Exploratory Factor Analysis (EFA) for the analysis of multivariate data. However, EFA is a tool intended to allow generate a new theory by exploring latent factors that best accounts for the variations and interrelationships of the manifest variables, while PCA is used to summarize the information available from the given set of variables and reduce it into a fewer number of components [28]. In our study, PCA is deemed more appropriate since no specific theory behind the relationships among the variables under consideration is developed and the ultimate goal is to retrieve a single factor/component representing the level of individual physical health status. Centralized data and covariance matrix have been considered for the analysis purposes [29], while the combined use of discrete and ordinal data to applications of PCA is supported by literature [29-31], especially for exploring high-dimensional datasets with a small number of non-continuous variables.

In **Table 1**, the mean values and standard deviations of the health-related measures under consideration

Table 1. Means and standard deviations (SD) of the health variables under consideration for the first imputed dataset.

	Activities of daily living	Chronic diseases	Instrumental activities of daily living	Mobility limitations	Self-perceived health
Mean	0.28	1.90	0.60	1.79	3.28
SD	0.96	1.65	1.65	2.47	1.05

are presented for the first imputed dataset. The mean values concerning ADL and IADL are the lowest ones observed (M = 0.28, SD = 0.96 and M = 0.60, SD = 1.65 respectively) indicating that individuals slightly suffer from limitations in their daily lives. Further, participants report on average two chronic diseases and mobility limitations as well (M = 1.90, SD = 1.65 and M = 1.79, SD = 2.47 respectively), while the average self-perceived health equals 3.28 (SD = 1.05), indicating a somewhat good subjective evaluation of their health. Similar results were obtained for the rest four imputed datasets (see **Supplementary** online material for further details).

The correlations among the health factors under consideration are presented in **Table 2**. The highest correlation value observed concerns ADL and IADL, and the lowest one is recorded among ADL and chronic diseases. As it concerns the other imputed datasets, similar results with slight differentiations were obtained (see **Supplementary** online material for further details).

It is worth noting here that, an important issue for any PCA setup, is how many principal components to retain. The selection is typically guided by the total variance explained and the relative sizes of eigenvalues (and/or the desirable number of components to be kept) [32]. Although extracting two components accounted for 83% of the variability in the original data, in this study we have retained only the first component (PC1) as it explains a quite high percentage, approximately 68%, of the total variance (with a corresponding eigenvalue equal to 9.21), thus obtaining a single index for an individual's overall physical health status assessment. Similar proportions and eigenvalues have been obtained for the rest imputed datasets as well. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was equal to 0.77, and Bartlett's test of sphericity was statistically significant (p-value < 0.001), meaning that the sample from which these data were collected was adequate and the variables under consideration suitable for structure detection. Factorability of the data was also assessed for the rest imputed datasets, and similar results were obtained with those of the first imputed dataset. The selected component weights are presented in the following equation:

$$\begin{aligned}\mathrm{PC1}_i &= 0.22*\mathrm{ADL}_i + 0.34*\text{chronic diseases}_i + 0.42*\mathrm{IADL}_i \\ &+ 0.78*\text{mobility limitations}_i + 0.21*\mathrm{SPH}_i, i = 1,..,N.\end{aligned}$$

The weights are positive for all measures under consideration, and mobility factor is observed to have the highest component weight followed by IADL, the number of chronic diseases, ADL, while SPH follows last. These weights, from a numerical point of view, are equal to the coefficients of the variables, and provide information about which variables give the largest contribution to the component. As regards the interpretation of the retrieved component, it represents an overall physical health metric/index for which the higher the score for an individual, the worst health level.

2.3.3. Predictors

The Big Five personality traits (*i.e.*, openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism) represent here the explanatory/predictor variables under study. These range among two extreme conditions (in a scale of 5 units regarding each personality dimension) based on the information included in the release guide of SHARE for wave 7 [24]. Specifically, openness to experience includes the conditions (1) "I see myself as someone who has few artistic interests" and (2) "I see myself as someone who has an active imagination". Conscientiousness is referred to the two next conditions, (1) "I

Table 2. Correlations between the health variables under consideration for the first imputed dataset.

	Activities of daily living	Chronic diseases	Instrumental activities of daily living	Mobility limitations	Self-perceived health
Activities of daily living	1.00	0.27***	0.74***	0.60***	0.32***
Chronic diseases		1.00	0.30***	0.50***	0.49***
Instrumental activities of daily living			1.00	0.64***	0.37***
Mobility limitations				1.00	0.54***
Self-perceived health					1.00

***p-value < 0.001.

see myself as someone who tends to be lazy" and (2) "I see myself as someone who does a thorough job", whereas extraversion includes (1) "I see myself as someone who is reserved" and (2) "I see myself as someone who is outgoing, sociable". Finally, the following two conditions, (1) "I see myself as someone who is generally trusting" and (2) "I see myself as someone who tends to find fault with others" represent the characteristic of agreeableness, while the conditions (1) "I see myself as someone who is relaxed, handles stress well" and (2) "I see myself as someone who gets nervous easily" illustrate the dimension of neuroticism.

2.3.4. Controls

Based on the study design, we control for age of the respondents at the time of interview (measured in years), gender (female is the reference category), and country of residence (Austria is the reference category). The choice of controls aligns with common demographic factors known to influence health outcomes and typically retrieved from large social science panel studies (such as the SHARE cross-sectional panel dataset used in this paper).

2.4. Data Analysis

For the analysis purposes, firstly, PCA has been implemented to obtain a single factor/component representing the level of individual physical health status. Afterwards, a dichotomization process was applied to the retrieved PCA scores to obtain a two-group discrimination, representing a good or bad health status of respondents. The process of dichotomization is typically adopted in medical applications either to classify patients according to the risk they face or make a decision about the potential necessity of additional diagnostic testing [33, 34]. Nelson *et al.* [35] provided mathematical evidence that through maximizing Youden's statistic, the best choice for binary thresholding is achieved. Further, in several diagnostic studies, Receiving Operating Characteristics (ROC) curves constitute the most widely used tool to evaluate a binary outcome and provide a graphical plot that illustrates the performance of a binary classifier model. In this study, we are interested to separate scores in two groups based on better or worse health levels respondents exhibit, and the conversion of PCA scores in a binary form was succeeded using coordinates of the ROC curves (sensitivity, and 1-specificity) and Youden's index through the maximization of the index value [sensitivity-(1-specificity)]. This index is used to select the appropriate cut-off point when a diagnostic test gives a numeric result rather than a dichotomous one [36]. Further, this binary health indicator has been used for building binary logistic regression (LR) models for the total sample as whole, and then separately by age group. The method of binary logistic regression is typically adopted to model the relationship between a binary dependent variable and a set of independent variables that are either categorical or continuous [37], and is widely used for practical classification problems in various scientific fields including medical and social sciences. For instance, the probability of a certain event taking place such as a patient being healthy or suffering from a given disease based on his/her medical history can be modelled using logistic regression method [38, 39].

Assessing the fulfillment of assumptions in statistical analyses involved and the aforementioned stages of the data analysis process (PCA, ROC analysis, and LR modelling) were executed in IBM SPSS Statistics (v. 20) for all imputed datasets. In order to ensure the findings' reliability, robustness of results across different software programs was examined. The use of Statgraphics (v. 5) package also provided transparency in the software utilized as an alternative choice and yielded similar results for all data analysis methods employed in this paper. For simplicity of the discussion, results are presented here in detail only after executing SPSS analyses for the first imputed dataset, while for the rest the interested reader may refer to the **Supplementary** online material.

3. RESULTS

As aforementioned, a dichotomization process was applied to the retrieved PCA scores in order to obtain a two-group discrimination (good or bad health status) of SHARE participants as regards their physical health condition (the cut-off point for the total sample equals 1.84723). **Table 3** shows the relative and absolute frequency distribution of the health status of SHARE respondents with better (PCA scores lower than 1.84723) and worse (PCA scores higher than 1.84723) physical health as well. The results are presented for the total study sample and for each age group separately. Results indicate that respondents having better or worse physical health status share an almost identical proportion (around 50%) as regards the total sample. Comparisons made by age group reveal that participants aged 50 - 64 exhibit a good physical health status in a higher proportion (65.9%). Further, as regards respondents aged 65 - 79, the ratio among those displaying higher and lower values for the physical health index is shared in almost equal portions, while there is a slight precedence in those exhibiting worse physical health (about 54%) against those with a better physical health condition (about 46%). However, the percentage of those having better physical health decreases drastically for individuals aged 80 years or higher (almost 20%), a result expected for those in advanced age. Similar relative frequencies for the physical health index were obtained for the rest imputed datasets (see **Supplementary** online material for further details).

Table 4 displays the descriptive statistics for all variables under consideration for the total sample of respondents and by age group separately. The study sample consists of 75,700 individuals with mean age of 68.70 years (SD = 9.81), while women (56.8%) hold a slight lead compared to men (43.2%). In addition, among age groups, the sample of individuals aged 65 - 79 has the highest frequency (35,375 observations) whereas the sample of oldest old participants has the lowest one (11923 observations). Results also indicate that females outnumber males, especially for the first and third age group. As regards the Big Five personality characteristics, for the whole sample, in a scale of 1 (lower value) to 5 (higher value), the highest mean value refers to conscientiousness (M = 4.12, SD = 0.80) and the lowest refers to neuroticism (M = 2.66, SD = 1.01). Agreeableness (M = 3.65, SD = 0.83), extraversion (M = 3.48, SD = 0.92) and openness (M = 3.28, SD = 0.94) share almost similar values. The respective results obtained for each age group are roughly the same compared to the total study sample. For all age groups, individuals are low in neuroticism

Table 3. Relative and absolute (into parentheses) frequency distribution of the physical health status for the first imputed dataset.

Percentages	Total sample (N = 75,700)	Age group 50 - 64 (N = 28,402)	Age group 65 - 79 (N = 35,375)	Age group 80 - 105 (N = 11,923)
Better physical health status	49.4% (37,375)	65.9% (18,720)	45.9% (16,253)	20.2% (2403)
Worse physical health status	50.6% (38,325)	34.1% (9682)	54.1% (19,122)	79.8% (9520)

Notes: Cut-off point derived from ROC curves analysis equals 1.84723. N denotes sample size.

Table 4. Descriptive statistics (means, and standard deviations into parentheses) of the variables under study for the first imputed dataset.

Predictors	Total sample	Age group 50 - 64	Age group 65 - 79	Age group 80 - 105
Controls				
Age at the time of interview	68.70 (9.81)	58.79 (3.69)	71.27(4.22)	84.71(3.99)
Gender				
Men	43.2% (32,735)	41.7% (11,854)	45.2% (15,995)	41.0% (4886)
Women	56.8% (42,966)	58.3% (16,548)	54.8% (19,380)	59.0% (7038)
Big Five Personality Traits				
Extraversion	3.48 (0.92)	3.51 (0.92)	3.47 (0.92)	3.41 (0.93)
Agreeableness	3.65 (0.83)	3.62 (0.84)	3.66 (0.83)	3.73 (0.82)
Conscientiousness	4.12 (0.80)	4.13 (0.80)	4.12 (0.80)	4.08 (0.82)
Neuroticism	2.66 (1.01)	2.67 (1.00)	2.66 (1.01)	2.65 (0.99)
Openness	3.28 (0.94)	3.34 (0.92)	3.28 (0.95)	3.15 (0.94)
Number of respondents	75,700	28,402	35,375	11,923

(M = 2.67, SD = 1.00 for the first group, M = 2.66, SD = 1.01 for the second group, and M = 2.65, SD = 0.99 for the third group, respectively) and high in conscientiousness, especially those belonging in the first (M = 4.13, SD = 0.80) and second (M = 4.12, SD = 0.80) age group. In addition, participants aged 50 - 64 are more extraverted (M = 3.51, SD = 0.92) and opened to experiences (M = 3.34, SD = 0.92), whereas the oldest old more agreeable (M = 3.73, SD = 0.82). Finally, for individuals aged 65-79, the mean values among all Big Five personality traits range at a moderate level as compared to the other two age groups. The previous descriptive measures are also representative of the rest imputed datasets (see **Supplementary** online material for further details).

The results obtained through LR modelling are displayed in **Table 5**. In particular, the odds ratios (along with 95% confidence intervals) for the physical health index constructed are given for both the total study sample and each age group separately. Age was found to be a significant predictor of physical health, increasing the odds of reporting a worse physical health status for the total population by 8.9%. The Big Five personality traits were also found to be significant predictors for worse physical health condition levels for the total study sample. Specifically, high levels of neuroticism increase the odds of having a bad physical health status by 36.9%, whereas for the remaining traits, results are more encouraging. Individuals being extraverted present a 2.5% lower relative risk of bad physical health levels based on the index constructed, whereas those being opened to experiences report a somehow better health status since the risk is reduced by 6.4%. Further, the more conscious are the people, the less are the chances of worse physical health levels (the odds decrease by 14.8%). Contrary to that, for respondents being more agreeable, an increased likelihood of suffering from poor physical health is observed (the odds increase by 3.2%). The results obtained after exploring those relative risks between different age groups did not reveal substantial differences among the second and third age group, whereas this is not the case for the first age group. For instance, the index of physical health status for participants aged 50 - 64 seems to be only affected by neuroticism and conscientiousness. Especially, neuroticism causes the highest increase of relative risk for a worse physical health status among all age groups and the total sample, and equals 44% as it concerns the first age group. Being extraverted, opened to experiences and conscious are protective factors of better physical health mainly for the oldest old participants, over 80 years. Finally, the impact of neuroticism is the lowest one for individuals being over 65 and up to 79 years. Further, among all age groups, men show

Table 5. **Odds ratios (along with 95% confidence intervals into parentheses) for the physical health index constructed—Results for the total study sample and by age group for the first imputed dataset[a].**

Predictors	Total sample	Age group 50 - 64	Age group 65 - 79	Age group 80 - 105
Controls				
Age at the time of interview	1.09** (1.087, 1.090)			
Gender				
Women (ref.cat.)	1	1	1	1
Men	0.64** (0.622, 0.664)	0.77** (0.735, 0.816)	0.62** (0.597, 0.652)	0.47** (0.424, 0.513)
Big Five Personality Traits				
Extraversion	0.98** (0.957, 0.993)	1.00 (0.972, 1.032)	0.95** (0.929, 0.977)	0.91** (0.866, 0.965)
Agreeableness	1.03** (1.011, 1.053)	1.03 (0.995, 1.063)	1.03* (1.005, 1.064)	1.08* (1.015, 1.146)
Conscientiousness	0.85** (0.835, 0.870)	0.88** (0.847, 0.905)	0.85** (0.827, 0.875)	0.82** (0.766, 0.868)
Neuroticism	1.37** (1.346, 1.393)	1.44** (1.400, 1.480)	1.30** (1.271, 1.332)	1.37** (1.296, 1.440)
Openness	0.94** (0.920, 0.953)	0.99 (0.963, 1.019)	0.91** (0.886, 0.929)	0.86** (0.815, 0.904)
Number of respondents	75,700	28,402	35,375	11,923

Note: ***p*-value < 0.01, **p*-value < 0.05. [a]All models were controlled for country of residence.

lower risk of having a worse physical health status compared to women, and especially for the third age group, the oldest old males present 53.4% lower odds of a worst physical health condition compared to females. Previous results are in accordance with those obtained from the rest imputed datasets, even though there are slight numeric differences among the predictors (see **Supplementary** online material for further details).

4. DISCUSSION

The relationship between health status and the Big Five personality traits has already been widely studied [3-6, 40]. However, to the best of our knowledge, none of previous studies has considered the "combined effect" of already established subjective and objective health-related measures, and further estimated the impact and protective role of personality dimensions on a one health index designed for an overall assessment of older Europeans' physical health status. As a result, the present study, through adopting PCA and taking into consideration a linear combination of concurrent health-related factors, reduced the computational expense of exploring all the main effects and their interactions, further controlling the error introduced due to multiple testing [41, 42]. The retrieved component is interpreted as an index measuring the physical health status of respondents. Further, the predictive significance of Big Five personality characteristics and their protective role for physical health is here examined for older Europeans, and although past research has already supported a significant relation of Big Five traits with age [15-17], the present study focused on examining age groups differences, making meaningful comparisons through the classification of three age groups for risk stratification purposes, a methodological approach supported by other researchers as well [43].

Our findings suggest that, the younger respondents, up to 64 years, have better physical health status compared to those aged 65 up to 79 years and especially the oldest old who present the worst physical health levels as expected. As aforementioned, the physical health status of older Europeans is here measured considering an index constructed for overall health assessment, combining five health-related measures (chronic diseases, mobility limitations, ADL, IADL, and SPH) contrary to previous studies mainly exploring the association of age with these health factors individually. For instance, Al Senany and Al Saif [44] supported that ADL are positively correlated with age, and later Gobbens [45] found that the percentages of adults over 75 years suffering from ADL and IADL were 54.6% and 67.4% respectively. Two years later, Ćwirlej-Sozańska *et al.* [46] took similar measurements regarding limitations for individuals aged 75 and older but the frequency of those suffering from IADL were clearly higher (57.31%) compared to those dealing with ADL (30.37%). Further, Mourão *et al.* [47] pinpointed the presence of chronic diseases in the population of adults aged 65 and older in quite high frequencies, especially for those referring to hypertension (62.1%) and arthritis (43.5%). Contrary to the results obtained as regards ADL and IADL limitations, and chronic diseases as well, older adults generally self-rate their health as good, mainly those belonging to the age group of 65 to 79 years [48].

Furthermore, for the total study sample, our findings suggest that Big Five personality traits significantly predict the physical health status, especially the characteristic of neuroticism. Not by accident, the personality trait of neuroticism is associated with health-related quality of life [49] and has been already characterized as the predictor of quality and longevity of human lives [50]. Hudek-Knezević and Kardum [51] found that this trait significantly predicts the presence of chronic illnesses. International literature though, supports the linkage among agreeableness, conscientiousness, and extraversion as predictors of self-rated health [52], whereas other research sources provide limited evidence that extraversion and openness may be related with greater lifespan [53]. Cheng *et al.* [54] pointed out that extraverted individuals reported a more positive perspective as regards someone's worldview and enhanced levels for quality of life, whereas neuroticism had an interrelation with a less optimistic perspective and poorer health.

Regarding the first age group including midlife adults between 50 and 64 years, traits of conscientiousness and neuroticism were the only significant predictors of physical health. Further, all Big Five characteristics were found to significantly predict the physical health levels of respondents belonging to the second age group, including older adults among 65 to 79 years. The latter findings also hold for the oldest old Europeans. It is worth noting here that past studies have thoroughly supported the association among the Big Five traits and age, showing that neuroticism and extraversion are negatively related to age whereas agreeableness and conscientiousness are positively associated, while openness to experience take the highest values in midlife [15, 16, 55]. In this context, the present analysis shed light to differences among age groups, highlighting the significance of each personality dimension across lifespan.

4.1. Limitations

This study is subject to some limitations that should be mentioned to avoid misleading conclusions. First, research data are based on self-reported answers and refer to respondents' self-perceived health-related characteristics, and thus they may span recall errors. Second, the index constructed for overall physical health assessment takes into consideration concurrent physical health-related factors but not hereditary, retrospective, or mental health predictors since such related information are not sufficiently available in the SHARE Wave 7 database used for this research purposes. Third, the present findings are based on cross-sectional data and a correlational study design, not allowing us drawing conclusions as regards the causal explanation of how personality traits affect physical health. Fourth, the application of PCA has some limitations itself that should be considered when interpreting the results. In particular, the resulting components are not easy to be described or comprehended compared to the original variables included in the analysis. Nevertheless, PCA allowed us here to handle multicollinearity that holds when two or more variables are strongly correlated, identify a one health index for overall physical health assessment, increase the interpretability of the LR model-derived results, while preserving the maximum amount of information of the available multidimensional data. Finally, this research findings are discussed based on the results derived only from the first imputed dataset, thus this may yield a kind of bias in findings' interpretation. However, looking at the outcomes of the rest imputed datasets, only slight differences are observed.

4.2. Conclusion and Future Directions

Despite the aforementioned limitations, this study provides evidence on how personality traits affect the physical health status of older Europeans and suggests an overall health assessment achieved by taking into consideration the combined effect of well-established subjective and objective health-related indices such as the number of chronic diseases and mobility limitations, ADL, IADL, and SPH; thus, the findings presented have important clinical implications. Neuroticism is the most significant predictor of physical health for all age groups under consideration, while conscientiousness was found to have a highly significant impact on health levels for oldest old. Extraversion and agreeableness also predict the constructed physical health index, whereas openness matters the most as regards older adults and oldest old participants. It is therefore evident that personality is a key risk factor in preventive health care. However, even if the odds of reporting a worse physical health status in relation to age and each personality trait were estimated here, future research should further investigate mental health predictors, hereditary characteristics, and childhood data in the construction of an overall health index representing health as a state of complete physical, mental, and social well-being. Further, it would be of great interest a lifespan approach for exploring the associations among personality and health factors longitudinally. Thus, future research should focus on investigating these paths in a longitudinal fashion to further achieve causal explanations. Likewise, it is of great interest to evaluate the impact of personality traits on Europeans' health levels, taking into account the differences emerged from various characteristics and contexts under consideration such as gender characteristics, educational attainment, country of residence, healthcare systems or other socioeconomic and demographic predictors. Finally, for future research expansion, it would be insightful to investigate the efficacy of supervised learning techniques (such as partial least squares regression) instead of unsupervised techniques (like PCA) aiming to discern whether there is an augmentation in modeling performance accuracy under the application of these different methodologies. Likewise, comparing the performance of LR classifier over other common binary classification and discrimination methods would strengthen the employed methodological approach.

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For this postdoc research study, we did not obtain approval from the Ethics Committee/Institutional Review Board of Panteion University of Social and Political Sciences since only secondary data were used for analysis purposes. The analytic code for statistical analyses can be found in the **Supplementary** online material. The ideas and data appearing in the manuscript have not been disseminated before.

AUTHOR'S CONTRIBUTION

Conceptualization: ES; Data curation: ES; Formal analysis: ES; Methodology: ES; Supervision: CP; Validation: ES; Visualization: ES; Writing-original draft: ES; Writing-review and editing: CP.

PUBLIC SIGNIFICANCE STATEMENT

This study examines the impact of "Big Five" across the life span of Europeans aged 50 or higher by estimating the odds of reporting a better/worse physical health status in relation to different age groups and each personality trait including extraversion, agreeableness, openness to experience, conscientiousness, and neuroticism. Findings provide generic answers about how personality psychology should be translated to allow personalizing preventive health care and medicine for patients.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest regarding the publication of this paper.

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SUPPLEMENTARY

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