Health and quality of life in ageing populations: A structural equation modelling approach

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Abstract

Higher life expectancy and lower fertility rates are changing the global population structure, leading to a fast-growing ageing society. To face this societal challenge, governments worldwide are increasing public expenditures focusing on healthy ageing. The objective of these investments is to increase quality of life among older people. However, there is a lack of studies focused on understanding the extent to which a wide range of demographic, socioeconomic and health characteristics are associated with quality of life in advanced ages. Therefore, the objective of this paper is to explore the role of a variety of factors towards quality of life, with a particular focus on health. Structural Equation Modelling (SEM) is employed using Stata 16 to explore these associations, using data drawn from the Survey of Health, Ageing and Retirement in Europe (SHARE). Contrary to many studies which use self-assessed single-item questions or additive indices to measure unobserved concepts, such as health and quality of life, this paper models such constructs as latent variables. Moreover, a minor contribution of this paper is to employ standard statistical techniques using additive indices along with the main SEM estimation. As the theory predicts, estimates found with additive indices are downward biased compared to latent variables, but so far, there are no studies showing this empirical exercise. The overall findings suggest that non-pecuniary factors, especially physical health status and participating in social activities, play a larger role in enhancing quality of life in advanced age compared to pecuniary factors such as income and financial assets. Therefore, greater attention should be paid on non-economic factors to enrich quality of life among an increasingly ageing population.

JEL codes: C3 – C51 – I1 – J14

Key words: health; quality of life; structural equation modelling; Stata

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Data Availability Statement: Please note that the analysis was based on the SHARE (Survey of Health, Ageing, and Retirement) dataset. Data can only be accessed upon request, with detailed information about this process available here: http://www.share-project.org/data-access/shareconditions-of-use.html.

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1. **Introduction**

The global population is undergoing an unprecedented ageing process, representing a major challenge for governments in developed and developing countries (United Nations, 2019). In Europe, the joint effect of higher life expectancy and lower fertility rates is changing the European population structure (European Commission, 2018). Responding to this, the European Union has increased investments in projects focused on healthy ageing. For example, the EU has allocated grants under the Horizon2020 supporting better health and higher quality of life of older adults. Among rapidly ageing societies, the improvement of quality of life in advanced age is not only a key public policy issue for policymakers (OECD, 2013; Steptoe et al., 2015; Van Leeuwen et al., 2019), but it is also relevant to all of society being an ultimate goal of people's lives (Frey and Stutzer, 2002; López Ulloa et al., 2013). Despite the international agreement on the importance of quality of life among older adults, there are ongoing debates regarding how to define and assess quality of life (Bulamu et al., 2015; WHO, 2015).

These debates are nourished by the literature related to measurement issues of unobservable concepts (e.g. Bollen and Bauldry, 2011; Braun and Mislevy, 2005; McNeish and Gordon Wolf, 2020). There is an on-going debate about how to assess multi-dimensional constructs which cannot be directly measured through observed data, such as health and quality of life. A stream of studies employs self-assessed single-item questionnaires as proxies of unobservable constructs. For example, quality of life is sometimes proxied with the single question "How satisfied are you with your life?" (e.g. Collins et al., 2008; Deaton, 2008; Graham et al., 2011). However, there is still debate around the validity of subjective variables (Althubaiti, 2016), and, considering the complex nature of such constructs, it might be reasonable to think that a single answer may not capture such multi-dimensional concepts (McNeish and Gordon Wolf, 2020). As a result, a series of additive indices have been developed to better measure multi-dimensional constructs. Relevant to this study, quality of life is often measured through the CASP-19 index which is an additive index of questions related to different aspects of quality of life specific to older people (Hyde et al., 2003). However, some have also questioned the validity of such additive indices for measuring unobservable concepts, which are indirectly observed through self-assessed questions in survey questionnaires (Bollen, 1989; Bollen and Lennox, 1991).

Another way to measure complex unobserved constructs when self-assessed items are included in the analysis is using latent variables. Latent variables represent the unobserved concept underlying a set of observed variables, capturing their shared variance while excluding the unique measurement error of self-assessed observed items (McNeish and Gordon Wolf, 2020, Salkind, 2010). Similar to a machine learning technique, latent variables are formed with a data-driven approach, hence, the selection of the observed items composing each latent construct is driven by the data analysed.

Despite the importance of understanding the determinants of quality of life, there is a lack of studies exploring the relationship between a wide range of individual characteristics and quality of life (Raggi et al., 2016). Most of the research within economics is focused on economic variables such as income and economic status, suggesting that these have the greatest lasting effects on quality of life (e.g. Blanchflower and Oswald, 2004; Deaton, 2008; Inglehart and Klingemann, 2000). Attention to the role of non-pecuniary factors is increasing, with studies attempting to analyse the role of demographic characteristics in influencing quality of life. These specifically focus on age (Blanchflower and Oswald, 2008; Cheng et al., 2017; Van Landeghem, 2012), gender (Green et al., 2018; Kahneman and Deaton, 2010; Sousa-Poza and Sousa-Poza, 2003; Stevenson and Wolfers, 2009) and education (Clark, 2018; Clark and Oswald, 1994). Health has also gained popularity to explain quality of life especially in advanced age. However, several studies focus only on specific aspects of it. For instance, Weber et al. (2015) and Freedman et al. (2017) consider only physical health and find that it has a strong and positive association with quality of life in advanced age, which is also confirmed by a systematic review of Fortin et al. (2004). Other authors focus only on cognitive aspects of health, showing that cognitive deterioration contributes to lower quality of life (Allerhand et al., 2014; Comijs et al., 2005; Jetten, 2010; Pan et al., 2015). Other studies addressing health as a determinant of quality of life generally focus only on specific health dimensions, such as visual impairment (Xiang et al., 2020); obesity (Dale et al., 2013); or on behavioural issues, like alcohol use (Van Dijk et al., 2004), smoking (Vogl et al., 2012) and active lifestyle (Rosenkranz et al., 2013).

Little research has been conducted so far around the impact of the overall health status on quality of life. To my knowledge, only Graham et al. (2011) study the determinants of quality of life considering the overall health of the respondents while also accounting for some socio-economic variables. However, these authors employ standard linear regressions in their analysis, measuring health and quality of life with self-assessed single-item or additive indices. Mataria et al. (2009) use a structural equation modelling approach to assess the effects of demographic and socio-economic variables on specific quality of life dimensions yet health is not included among its predictors. SEM is increasingly popular within social science disciplines such as gerontology and psychology, where several studies implemented this statistical method to understand the role of health towards quality of life using latent variables (Cho et al., 2011; Hirve et al., 2014; Ponce de León et al., 2020; Xiang et al., 2020). However, these studies do not include other factors that might be relevant for quality of life.

Importantly, a stream of studies employs multiple causes multiple indicators (MIMIC) models, which is a special case of SEM, to measure unobservable constructs. Several papers have employed MIMIC models of health and healthcare utilisation, but this methodology was mainly limited to the measurement of the unobserved construct itself without estimating the effect of one latent variable on another (Wagstaff, 1986; Wagstaff, 1993; Wolfe and Van der Gaag, 1981). However, researchers stopped using these methods due to their high computational complexity. Yet, the recent availability of high performing machines and dedicated packages in popular statistical software, such as Stata, contributed to a resurgence of interest in the use of SEM related techniques.[2] (e.g., see Tarka, 2018).

Understanding which domains enrich quality of life in advanced age is important in shaping policy proposals and advising individuals on how to allocate private and public resources given an ever-increasing age-related spending. Hence, this paper contributes to the current literature providing an understanding of a wide set of factors associated to quality of life among older populations using a structural equation modelling approach with latent variables. Minor contribution of the paper is also to show a direct comparison between a SEM framework with latent variables and standard linear regressions with additive indices. Since additive indices assume that observed self-assessed items are perfectly measured, they fail to account for measurement errors leading to downward biased estimates due to attenuation (Kline, 2016). In line with the theory, this paper shows that SEM with latent variables might be a better technique to explore unobservable constructs indirectly measured with self-assessed observed items.

2. **Data**

The data analysed in this paper are drawn from the Survey of Health, Ageing and Retirement in Europe (SHARE), which is a longitudinal survey including rich individual-level information about health, employment, housing and socio-economic status (Borsh-Supan and Jurges, 2005). Each wave

[2] SEM started to re-gain popularity in empirical applications with the availability of freeware packages related to R such as LAVAAN (Rosseel, 2012) and the SEM feature of Stata introduced with Stata 12 in 2011.

of SHARE is collected every two years, with eight waves currently available from Wave 1 (2004) until Wave 8 (2020). Only people older than 50 years old are eligible for the survey, together with their spouses or partners regardless of their age[3].

2.1 Variables used in the analysis

Cognition. The latent variable of cognition is formed using data available in SHARE regarding the cognitive tests that SHARE interviewers performed on the survey participants. In specific, the tests retained to form the latent factor are: word recall (immediate and delayed), verbal fluency and math skills (Table 1A). Variables have been recoded so that higher scores mean better cognitive ability.

Physical health. SHARE includes several additive indices of physical health status, with their respective items, which are commonly used in the literature as proxies for assessing the physical status of respondents (e.g. Coe and Zamarro, 2011; Yaffe et al., 2010). Since the latent variable of physical health should not involve any cognitive abilities, this paper considers the items related to mobility limitations (i.e. a detailed set of binary questions about difficulties in mobility - see Table 2A, Appendix) for measuring the latent variable of physical health. This choice is also supported by the fact that in advanced age, physical status and mobility can be considered closely related (Rosso et al., 2013; Webber et al., 2010). Conceptually, we can think of physical health as an underlying concept proxied by the different levels of mobility among individuals, where a higher physical health status corresponds to perfect mobility. Moreover, since all mobility items are self-assessed, a latent variable might be more appropriate than a composite index accounting for the measurement error which might be present.

Quality of life. SHARE contains CASP-12, a modified version of the original CASP-19 self-completion questionnaire designed to measure quality of life of older individuals across the four domains of Control; Autonomy; Self-realisation; and Pleasure (Hyde et al., 2003). More specifically, within each CASP-12 domain, respondents are asked to answer to three questions rating how often they experience specific feelings on a 4-point scale (ranging from often to never). The overall score, which is the sum of all the items, form the additive index which is usually used as an instrument to assess the respondents' quality of life (Gale et al., 2014; Okely et al., 2017; Pascual-Sáez et al., 2019). However, given the nature of quality of life, which might be better thought as being a latent factor rather than an observed variable, and the measurement problems related to the self-assessed questionnaire, this paper uses the CASP-12 items to form the latent construct of quality of life.

[3] Hospitalized patients are excluded from the sample as well as those who are unable to speak the local language.

When constructing the latent variable of quality of life with all the CASP-12 items, we should find a 4-factor model as proposed by the developers of the index. However, when the latent variable of quality of life is formed using all the CASP-12 items, a factor model with items loading on different domains is found, diverging from the original index. Other authors find the same conclusion for other populations (Hamren et al., 2015; Howel, 2012; Rodríguez-Blázquez et al., 2020; Sexton et al., 2013). Hence, the latent variable of quality of life is measured considering only the items related to self-realisation and pleasure (Tablea 3A, Appendix). As suggested by Sexton et al. (2013), pleasure and self-realisation involve the pursuit of happiness and personal fulfilment, capturing the hedonic aspect of well-being and individual life satisfaction. A latent variable constructed with these items makes the paper more comparable to other studies using single-item questions of life satisfaction or happiness as proxies for quality of life (Anand et al., 2015; Collins et al., 2008; Deaton, 2008; Graham et al., 2011).

Socioeconomic variables. Apart from the individual characteristics of age, gender, education and the economic variables of individual income and monetary assets, other observed variables are included since they represent factors which are usually thought to be associated with quality of life. These social factors are thought to have an influence in increasing one's quality of life especially in the ageing process, including marital status, household size (Kotwal et al., 2016; Rosso et al., 2013; Warner and Adams, 2016; Warner and Kelley-Moore, 2012), area of living and participating in social activities (Berkman et al., 2000; Rowe and Kahn, 1997). Details of these variables can be found in Table 4A in the Appendix.

2.2 Descriptive statistics

The analysed sample of this paper is composed of older Europeans, including only individuals who are not clinically depressed and who are not affected by severe cognitive or physical disorders[4]. In fact, clinical depression could directly impact quality of life (Wilson et al., 2013). Cognition would be influenced by chronic cognitive illnesses such as Alzheimer's disease, Parkinson disease and severe dementia. And physical ability would be impacted by serious physical illnesses such as cancer, osteoporosis and hip, femoral or other fractures (Okely et al., 2017; Perrino et al., 2010; Ponce de León et al., 2020). Therefore, if diagnosed patients are included in the sample, quality of life could be directly driven by these conditions, making it difficult to estimate the relationship of the other

[4] A further analysis conducted on all retired respondents, including also diagnosed patients, shows similar results to the main estimates (available upon request)

factors. Conventionally, older individuals have been defined as being 65 years old or older (Orimo et al., 2006) and therefore only participants of such age are retained in the final sample. Moreover, in order to avoid complications of endogenous labour supply, I considered in the analysis only individuals who declared to be retired. In fact, the working environment might be a source of work-related stress and job-related rewards which might influence quality of life (Babu et al., 2016; Tzeng et al., 2012). Hence, by considering only respondents who are retired, the possibility that quality of life is driven by the working environment is avoided, focusing entirely on the health and socio-economic factors of older individuals. Moreover, participants from Israel are excluded from the analysis since the timing of its data collection is different from that of the other countries and it is not geographically located in Europe.

The estimation represents a cross-sectional analysis conducted on SHARE Wave 4, 5 and 6. Waves 1-3 are not considered since cognitive tests have been performed from Wave 4 onwards; Wave 7 is not included due to missing values of the depression variable, asked to very few respondents; finally, Wave 8 became available after this estimation. Since the structural equation model is applied to one wave at a time, fitting the model on three separate waves is satisfactory enough to see how well the model performs. Descriptive statistics for the analysed sample are presented in Table 1.

Table 1 shows that the descriptive statistics are similar across the three waves analysed for all the baseline characteristics and for the main variables of interest, which are health aspects and quality of life. High income countries located in North Europe are always the greatest proportion, followed by Eastern countries and Mediterranean countries.

3. **Empirical Analysis**

The first step of the analysis is selecting the observed variables for each latent construct through i) Exploratory Factor Analysis. Following this, the full Structural Equation model can be performed. SEM consists of two parts: ii) the measurement model, which is also known as Confirmatory Factor Analysis (CFA), assessing how well the proposed model fits the analysed data; and iii) the structural model, which adds the hypothesised relationships among latent and observed variables. Stata version 16 is used to estimate all these steps of the analysis.

Table 1 Basic descriptive statistics for Wave 4, 5 and 6

		Wave 4		Wave 5		Wave 6	
	Values	**Mean**	SD	**Mean**	SD	**Mean**	SD
Quality of Life (index)	0-6	4.74	1.074	4.85	1.003	4.81	1.003
Cognition (index)	0-4	1.86	0.547	1.93	0.532	1.94	0.541
Physical status (index)	0-10	8.70	1.88	8.81	1.862	8.79	1.821
Gender	0-1	0.45	0.498	0.46	0.498	0.46	0.498
Years of education	0-25	10.35	4.259	10.82	4.243	10.76	4.331
Age	65-100+	73.40	6.431	73.39	6.449	73.62	6.504
Marital status	0-1	0.70	0.459	0.71	0.455	0.70	0.457
Household size	0-10+	1.92	0.812	1.90	0.724	1.95	0.827
Urban	0-1	0.42	0.493	0.42	0.493	0.41	0.491
Social activities	0-1	0.45	0.497	0.43	0.495	0.41	0.491
Country (%):							
North Europe		53.44%		61.59%		49.98%	
Mediterranean Europe		14.47%		15.43%		21.22%	
East Europe		32.09%		22.98%		28.79%	
Income (quintile)	1-5	3.01	1.398	3.02	1.402	3.03	1.399
Assets (quintile)	1-5	2.11	1.707	2.18	1.722	2.14	1.718
Tot obs.		14,066		17,678		19,284	

Note: Additive indices are presented in the descriptive statistics for cognition, physical status and quality of life. This is done to give a general summary those variables, without presenting the statistics of the single items composing each latent variable.

2.2 Exploratory Factor Analysis

Firstly, Exploratory Factor Analysis (EFA) is used to determine which indicators are selected to form each latent variable[5]. The observed items retained for each latent construct are the variables presented in the Data section. A detailed description of the selection of observed items to measure the latent variables of cognition, physical health and quality of life are provided in the Appendix (Tables 6A to 12A).

Here, the latent structure is a simple structure, meaning that conceptually related items are loading on a single latent variable ensuring in this way a clear conceptual interpretation of the latent construct. The Exploratory Factor Analysis is firstly conducted on SHARE wave 4, but given that it is a data-driven process, I also conducted the same EFA analysis on the other two waves (SHARE wave 5 and 6) to see if the same latent variables with the respective observed items are still obtained. Tables 13A – 16A of the Appendix shows that this is indeed the case, meaning that the factor structure of the latent variables is acceptable throughout all waves. The validity of the latent variables is assessed by the internal reliability index, also known as Cronbach's alpha, and by the composite reliability index, ρ (Table 5A, Appendix).

2.2 Measurement Model or Confirmatory Factor Analysis

The aim of the measurement part of SEM is assessing how well the proposed measurement model fits the data. If the fit of the measurement model is acceptable, the structural part of SEM is implemented. In order to assess the fit of the measurement model, goodness-of-fit statistics are estimated to measure how closely the model-implied covariance matrix matches the observed covariance matrix.

Table 2 shows the most commonly used statistics with their cut-off thresholds and the values for the measurement model in each wave. All the local fit statistics presented in Table 2 are acceptable, apart from the Chi-square index which is rejected. However, the Chi-square index is overly sensitive in model testing for large samples; hence, the rejection might be due to the sensitivity of this model-fit to large samples rather than a true rejection of the model (Fan et al., 1999). For this reason, common practice in SEM to justify retaining the model with large sample size is to ignore a failed Chi-square test as long as the other local fit tests are acceptable (Kline, 2016).

[5] The totality of elderly individuals is considered for the construction of latent variables to have latent variables valid for a wide sample of elderly individuals, and not only for the specific analysed sample of this research

Table 2: Fit statistics full measurement model on analysed samples of Wave 4, 5 and 6

	Cut-off value	Wave 4	Wave 5	Wave 6
Chi-square	P>0.001	P<0.001	P<0.001	P<0.001
RMSEA	≤0.08	0.046	0.048	0.049
CFI	≥0.9	0.920	0.916	0.915
SRMR	≤0.1	0.041	0.042	0.042

Note: RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; SRMR = Standardized Root Mean Squared Residual

2.2 Structural Equation Model

Following the measurement part of SEM, the structural model of Equation 1 is employed, assessing the role of health (η_{1i} , η_{2i}) and socio-economic factors (X_i , Z_i) towards quality of life (Υ_i) of elderly respondents:

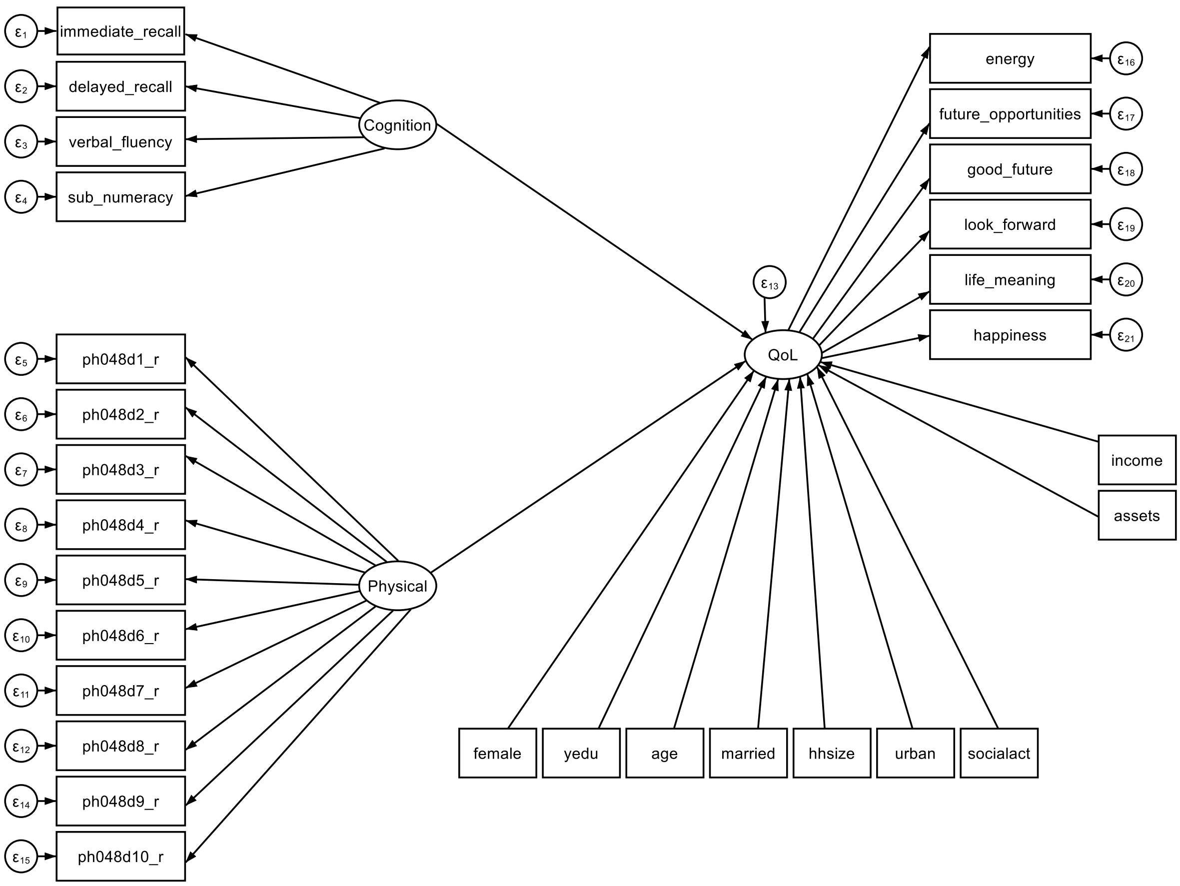
$$\Upsilon_i = \alpha_i + \gamma_1\eta_{1i} + \gamma_2\eta_{2i} + \gamma_3 X_i + \gamma_4 Z_i + \theta + \zeta_i \quad (1)$$

Where α_i is the intercept and ζ_i is the error term.

To fully understand the effect of each independent variable, the final model of (1) is implemented in four steps. Firstly, Model 1 only includes the latent variables of cognition (η_{1i}) and physical health status (η_{2i}) as predictors for the latent variable of quality of life (Υ_i). Model 2 adds a set of individual demographic variables (X_i) including gender, years of education, age, marital status, household size, area of living and social activities. Model 3 further adds a set of PPP adjusted economic variables (Z_i) including individual income and individual monetary assets, which comprise savings for long-term investments, bonds, stocks and mutual funds. In the last specification, country-fixed effects (θ) are further included to control for different socio-economic environments. A graphical representation of the full structural model is displayed in Figure 2.

Following the main SEM estimation, standard linear regressions with additive indices are performed as an empirical exercise. In this way, these two statistical techniques are compared to assess which one is more appropriate when complex unobserved constructs are analysed.

Figure 2 Graphical representation of the structural model



Note:
Covariation among all the independent variables is estimated but not pictured for ease of interpretation.
Conceptually related items only load on their respective latent variable.

4. **Results**

The default estimation for both SEM and linear regressions is based on complete case analysis. In case of an incomplete dataset, full information maximum likelihood (FIML) can be performed within the SEM framework, where the estimates are imputed using all the available information (Allison, 2003; Hoyle, 2012). If the proportion of missing data is very low, both complete case analysis and FIML will produce the same estimates (Kline, 2016). Here, despite the percentage of missing data (less than 5% for Model 1, just over 10% for Model 2, and around 40% when adding economic variables in Model 3), the remaining sample with complete information is still large enough to conduct a complete case analysis without risking losing statistical power. However, as suggested by Acock (2013), FIML is performed as sensitivity analysis to show that the estimates found when analysing complete cases are similar to FIML estimates, so the results are not biased due to the cases lost (Table 1B, Appendix). Another sensitivity analysis to control for non-normality in the dataset is conducted with robust standard errors, showing similar estimates to the main results (Table 2B, Appendix). To further check for any potential issues of multicollinearity among observed covariates correlation analysis (r) and variance inflation factor (VIF) are conducted prior to the estimation, showing no risk of high multicollinearity. These latter sensitivity analyses are available upon request.

The results of the main analysis are presented in Table 3 and Table 4. Table 3 shows the estimates found when using SEM with latent variables against the ones found when using additive indices in standard linear regressions. We can notice that for all the models in each wave analysed, the estimates found with additive indices are downward biased as the theory suggests (Kline, 2016). Composite indices formed with principal component analysis do slightly better than simple additive indices, but they are still smaller in magnitude compared to latent variable estimates. These results show that when we can conceptualise latent variables, they are more accurate in predicting the outcome variable compared to composite indices, as we can see from the magnitude of the estimates and of the error term.

Table 4 shows the results of the main analysis conducted using SEM with latent variables. According to these estimates, health is the factor with the highest association to quality of life with physical status contributing the most. This might be explained by the significant role that autonomy plays in older individuals, allowing them to retain their independence and social contacts (Rosso et al., 2013). Cognition is also positively associated with quality of life but to a lesser extent than physical ability. The estimates from the last specification show that on average across all waves, one standard deviation increase in cognition contributes to an increase in quality of life of around 0.1 standard deviation, and an increase in physical status leads to around 0.3 increase in quality of life. It can be noticed that, compared to the other factors included in the analysis, the overall health status plays the greatest role in enhancing older adults' well-being.

As expected, participating in social activities is always positively associated with quality of life. After health, it is the factor with the highest association to quality of life, contributing to the same extent as cognition. In fact, an increase of one standard deviation in social activities leads to around 0.15 standard deviation increase in quality of life. However, its magnitude is reduced when country fixed effects are included in the last specification.

The direction of the association of the other socio-economic variables included in the analysis is as expected, most of the coefficients are statistically significant but their magnitude is small, representing an impact of less than 0.1 standard deviation of quality of life.

Being female and having a higher education are both positively associated to quality of life, even if education is not always consistent being also negatively associated and statistically insignificant in Wave 5 and 6 when economic variables and country fixed effects are included. Interestingly, age is shown to be negatively associated to quality of life. This result is in line with the age-related decline of individuals contributing to lower health and in turn lower quality of life, but it goes against the widely documented age-related paradox of a U-shaped relationship (Blanchflower and Oswald, 2008; Easterlin, 2006). If that paradox was holding here, I should have found a positive association between age and quality of life since individuals aged 65 years old or older should be located in the upward sloping end of the U-shaped relationship. As expected from past research on loneliness among older individuals, being married and having many household members contributes to enhance quality of life (Warner and Adams, 2016; Warner and Kelley-Moore, 2012). Surprisingly, living in an urban area shows a negative association.

Finally, the economic variables of income and monetary assets are positively and significantly associated to quality of life. Specifically for wave 5 and wave 6, higher household income leads to an increase of around 0.2 standard deviation in quality of life which is almost of the same magnitude as the coefficient found with physical status. This might indicate that a higher financial stability contributes to less uncertainty for the future, leading to higher well-being. However, the role of economic variables is reduced in the last specification, where it can still be noticed that the increase of quality of life is mainly driven by the overall health status of the older respondents.

According to these results, individuals should allocate their resources on non-pecuniary factors such as maintaining good health and having a wide social network. These aspects seem to contribute the most to increased quality of life, while an emphasis on accumulating economic assets might not give the expected payoffs in increasing quality of life as people age. At a governmental level, social activities involving elderly individuals as well as health policies focused on enhancing their physical health might be effective in increasing quality of life in advanced age.

5. **Discussion and Conclusion**

There are some limitations to consider. Firstly, the direction of the relationship between health and quality of life is still widely debated. For instance, Danner et al. (2001) and Guven and Salouomides (2009) show that happiness contributes to longevity and others show that greater well-being contributes to better cognitive functions (Allerhand et al., 2014; Boyle et al., 2012; Llewellyn et al., 2008). However, when we consider these multi-dimensional concepts in their entirety, it is more likely that a poor overall health status affects individuals' quality of life rather than vice versa (Easterlin, 2003). Given that SEM is a confirmatory tool, this is also the hypothesis tested when fitting the proposed model to the analysed data.

Another limitation concerns the fact that structural equation modelling, as well as factor analysis, is heavily data based. Therefore, some might argue that the latent variables are only specific to the analysed sample. One way to overcome this concern is to do a cross-sectional validation as it is common practice also in machine learning techniques. I randomly divide the sample into two parts and I conduct the analysis on these two random subsamples separately (Table 17A - 21A, Appendix). On top of this analysis, I also considered participants present only in one wave, either Wave 5 or 6, to have a completely different dataset compared to Wave 4. All these sensitivity analyses confirm that the latent variables are acceptable (Table 22A - 26A, Appendix), even if there might still be a concern about the external validity of the results found. In fact, according to this research, the proposed SEM model is a good fit for the three waves of SHARE, but it might be possible that this SEM model does not fit well other data. Hence, the results found might not hold when considering different datasets. Since SHARE has comparable datasets from other countries, such as TILDA (The Irish Longitudinal Study on Ageing) and HRS (Health and Retirement Study), one way to overcome the external validity concern might be to conduct the same SEM analysis on these other datasets to see if the model is still acceptable.

This paper contributes to understand the role of a wide range of factors on quality of life among older adults. The results from the main analysis show that health, divided into the latent variables of cognition and physical status, is the major determinant of quality of life, with physical ability contributing the most. Participating in social activities has also a great effect. Interestingly, income and monetary assets do not contribute as much to individuals' quality of life in old age. Hence, individuals and policymakers should focus more on non-pecuniary aspects of older people's lives, such as increasing their physical health or widening their social network, rather than on accumulating economic resources which seem to not contribute as much to quality of life in advanced age. Minor contribution of the paper is also to provide an empirical exercise showing that the estimates found with composite variables are downward biased compared to latent variables. This suggests that when latent constructs can be conceptualised, structural equation modelling with latent variables should be used instead of standard regressions with additive indices, especially for analysing unobservable concepts measured with self-assessed items.

Table 3 Estimates of SEM with latent variables and of linear regression with additive indices

	Wave 4				Wave 5				Wave 6			
	Model 1	Model 2	Model 3	Country FE	Model 1	Model 2	Model 3	Country FE	Model 1	Model 2	Model 3	Country FE
Cognition (Latent)	**0.213**	**0.170**	**0.162**	**0.124**	**0.199**	**0.134**	**0.105**	**0.088**	**0.233**	**0.160**	**0.116**	**0.118**
Cognition (Add Index)	0.203	0.158	0.146	0.105	0.185	0.122	0.098	0.073	0.207	0.136	0.097	0.092
Cognition (pca Index)	0.209	0.164	0.154	0.116	0.196	0.133	0.111	0.086	0.217	0.147	0.108	0.104
Physical (Latent)	**0.334**	**0.309**	**0.299**	**0.269**	**0.333**	**0.304**	**0.282**	**0.276**	**0.306**	**0.283**	**0.259**	**0.249**
Physical (Add Index)	0.240	0.217	0.214	0.192	0.243	0.218	0.202	0.202	0.236	0.212	0.197	0.190
Physical (pca Index)	0.240	0.217	0.213	0.193	0.244	0.218	0.202	0.202	0.228	0.205	0.191	0.184
SEM error term	**0.811**	**0.784**	**0.779**	**0.675**	**0.817**	**0.773**	**0.718**	**0.660**	**0.822**	**0.776**	**0.730**	**0.660**
Regression error term	0.883	0.854	0.848	0.747	0.889	0.849	0.805	0.742	0.884	0.844	0.802	0.747
Error term with pca	0.879	0.852	0.846	0.756	0.882	0.844	0.798	0.746	0.883	0.844	0.804	0.748
Controls:												
Demographic Ch.		✓	✓	✓		✓	✓	✓		✓	✓	✓
Economic Variables			✓	✓			✓	✓			✓	✓
Country fixed effect				✓				✓				✓

Note: All the estimates are statistically significant, with p-value = 0.000

Table 4 Standardized results of main SEM analysis

	WAVE 4 **Structural equation models**				WAVE 5 **Structural equation models**				WAVE 6 **Structural equation models**			
	Model 1	Model 2	Model 3	Country FE	Model 1	Model 2	Model 3	Country FE	Model 1	Model 2	Model 3	Country FE
Cognition	**0.213**	**0.170**	**0.162**	**0.124**	**0.199**	**0.134**	**0.105**	**0.088**	**0.233**	**0.160**	**0.116**	**0.118**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical	**0.334**	**0.309**	**0.299**	**0.269**	**0.333**	**0.304**	**0.282**	**0.276**	**0.306**	**0.283**	**0.259**	**0.249**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female		**0.023**	0.013	**0.029**		**0.043**	**0.044**	**0.045**		**0.048**	**0.057**	**0.046**
		(0.022)	(0.286)	(0.010)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Education		**0.025**	0.015	**0.035**		**0.027**	0.004	0.016		**0.030**	-0.003	-0.003
		(0.013)	(0.220)	(0.005)		(0.002)	(0.669)	(0.152)		(0.000)	(0.781)	(0.794)
Age		-0.009	-0.011	**-0.037**		-0.012	-0.001	**-0.019**		**-0.032**	**-0.023**	**-0.032**
		(0.382)	(0.374)	(0.002)		(0.204)	(0.922)	(0.082)		(0.000)	(0.025)	(0.002)
Married		**0.054**	**0.047**	**0.038**		**0.073**	**0.067**	**0.049**		**0.072**	**0.059**	**0.061**
		(0.000)	(0.000)	(0.002)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Household size		**-0.045**	**-0.032**	0.015		**-0.019**	**0.027**	**0.039**		**-0.027**	**0.033**	0.010
		(0.000)	(0.013)	(0.233)		(0.048)	(0.022)	(0.001)		(0.002)	(0.002)	(0.340)
Urban		**-0.036**	**-0.046**	**-0.024**		-0.003	-0.015	-0.011		**-0.037**	**-0.051**	-0.006
		(0.000)	(0.000)	(0.028)		(0.752)	(0.108)	(0.235)		(0.000)	(0.000)	(0.500)
Social activities		**0.154**	**0.139**	**0.076**		**0.194**	**0.169**	**0.114**		**0.183**	**0.150**	**0.115**
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Income			0.005	**0.031**			**0.196**	**0.068**			**0.206**	**0.069**
			(0.676)	(0.034)			(0.000)	(0.000)			(0.000)	(0.000)
Assets			**0.089**	**0.033**			**0.071**	**0.049**			**0.074**	**0.038**
			(0.000)	(0.007)			(0.000)	(0.000)			(0.000)	(0.000)
N(obs)	N(13,568)	N(12,464)	N(8,814)	N(8,814)	N(16,927)	N(15,668)	N(10,871)	N(10,871)	N(18,790)	N(17,382)	N(12,371)	N(12,371)
Chi-squared	P<.001	P<.001	P<.001	P<.001	P<.001	P<.001	P<.001	P<.001	P<.001	P<.001	P<.001	P<.001
RMSEA	0.046	0.041	0.040	0.044	0.048	0.042	0.041	0.045	0.049	0.042	0.041	0.039
CFI	0.920	0.904	0.899	0.812	0.916	0.902	0.901	0.818	0.915	0.902	0.900	0.847
SRMR	0.041	0.035	0.034	0.031	0.042	0.035	0.035	0.033	0.042	0.035	0.034	0.027

Note: Cut-off values for fit indices: RMSEA≤.08; CFI≥.9; SRMR≤0.1
Income and Assets are in quintiles
p-values are in brackets, statistical significant estimates are in bold

Appendix

Table 1A SHARE variables for cognition

Latent variable	Observed indicators	Description	Value
	Immediate_recall	10 words list to recall immediately	0-10
Cognition	Delayed_recall	10 words list to recall after a period of time	0-10
	Verbal_fluency	Name as many animals as possible	0-100
	Sub_numeracy	Subtract a series of numbers	0-5

Note: Another math test which involves division instead of subtraction is present in SHARE, but it was administered to very few respondents hence I do not consider it due to data unavailability

Table 2A SHARE variables for physical status

Latent variable	Observed indicators	Description	Value
	Ph048d1_r	Difficulties: walking 100 meters	0-1
	Ph048d2_r	Difficulties: sitting two hours	0-1
	Ph048d3_r	Difficulties: getting up from chair	0-1
	Ph048d4_r	Difficulties: climbing several flights of stairs	0-1
Physical status	Ph048d5_r	Difficulties: climbing one flight of stairs	0-1
	Ph048d6_r	Difficulties: stooping, kneeling, crouching	0-1
	Ph048d7_r	Difficulties: reaching/extending arms above shoulder	0-1
	Ph048d8_r	Difficulties: pulling or pushing large objects	0-1
	Ph048d9_r	Difficulties: lifting or carrying weights over 5 kilos	0-1
	Ph048d10_r	Difficulties: picking up a small coin from a table	0-1

Note: Variables recoded so that higher scores mean better physical ability

Table 3A SHARE variables of CASP-12 for Quality of life

Latent variable	Dimensions	Observed indicators	Description	Value
	Control	Age_prevents	Age prevents you from doing	0-3
		Out_control	Feel what happens is out of your control	0-3
		Left_out	Feel left out of things	0-3
	Autonomy	Do_things	You can do things you want	0-3
Quality of life		Fam_responsib	Family responsibilities prevent you from doing	0-3
		Money_shortage	Shortage of money prevent you from doing	0-3
	Self-realisation	Energy	Feel full of energy	0-3
		Future_opportunities	Feel life is full of opportunities	0-3
		Good_future	Feel future looks good for you	0-3
	Pleasure	Look_forward	Look forward to each day	0-3
		Life_meaning	Feel life has meaning	0-3
		Happiness	Look back on life with happiness	0-3

Note: Variables recoded so that higher scores mean higher quality of life

Table 4A SHARE socio-economic variables

Observed indicators	Description	Value
Female	Gender: 1 is female, 0 male	0-1
Married	Marital status: 1 is married or with a partner, 0 otherwise	0-1
Urban	Area of living: 1 is living in a city or town, 0 indicates living in a rural area	0-1
Social activities	Social activities: 1 indicates that the respondents have participated in at least one activity among charity, sport, religion and political activities, 0 otherwise	0-1
Education	Years of education	0-25+
Age	Age of respondents	0-100+
Household size	Number of family members within the household	0-10+
Income	Individual income, PPP adjusted and coded as quintiles	1-5
Monetary assets	Individual amount of bonds, stocks, mutual funds, savings for long-term investments, PPP adjusted and coded as quintiles	1-5

Note: Economic variables are imputed firstly calculating the nominal value thanks to the exchange rate, and subsequently adjusting it to the purchasing power parity (PPP) index[6]. Individual PPP adjusted economic variables are calculated, dividing the economic variables by the number of household members. This is done since the income question is asked on a household level and the monetary assets are common to the same household members. Hence, economic variables at the individual level might be a more valuable information.

Table 5A Reliability indices for latent variables in each Wave

	Cut-off value	WAVE 4	WAVE 5	WAVE 6
Cognition				
Cronbach's alpha	$\alpha \geq .8$	0.80	0.80	0.80
Composite reliability	$\rho \geq .6$	0.65	0.66	0.66
Physical Status				
Cronbach's alpha	$\alpha \geq .8$	0.85	0.86	0.86
Composite reliability	$\rho \geq .6$	0.86	0.87	0.87
Quality of life				
Cronbach's alpha	$\alpha \geq .8$	0.82	0.82	0.84
Composite reliability	$\rho \geq .6$	0.83	0.83	0.84

Table 6A: Rotated factor loadings and unique variances of Cognition items

	Factor 1	Factor 2	Uniqueness
Reading_self		0.92	0.13
Writing_self		0.91	0.13
Memory_test		0.53	0.64
Orientation	0.39		0.79
Sub_numeracy	0.59	0.31	0.55
Immediate_recall	0.85		0.25
Delayed_recall	0.83		0.28
Verbal_fluency	0.67		0.47

Note: objective measurements of cognition reflect a single latent variable (Factor 1), hence, I retain these observed indicators

[6] PPP index based on the DataBank ICP, International Comparison Program, World Bank

Table 7A: Cronbach's alpha for Cognition

	Obs	Alpha
Orientation	29172	**0.800**
Sub_numeracy	29527	0.735
Immediate_recall	28674	0.678
Delayed_recall	28661	0.696
Verbal_fluency	28501	0.729
Test scale		0.772

Note: Cronbach's alpha indicates that if the orientation test is dropped, the overall reliability of the construct increases to 0.8 (which is the accepted threshold)

Table 8A: Rotate factor loadings and unique variances of Physical items

Difficulties in:		Factor 1	Uniqueness
Walking 100 mt	Item1	0.70	0.51
Sitting 2 hours	Item2	0.53	0.72
Getting up from chair	Item3	0.68	0.54
Climbing several flights of stairs	Item4	0.70	0.51
Climbing one flight of stairs	Item5	0.70	0.51
Kneeling, crouching	Item6	0.68	0.54
Extend arms above shoulder	Item7	0.60	0.64
Pulling or pushing large objects	Item8	0.73	0.47
Lifting or carrying weights over 5 kilos	Item9	0.72	0.48
Picking up a coin from a table	Item10	0.46	0.79

Note: all items load on a single Factor

Table 9A: Cronbach's alpha for Physical

Difficulties in:		Obs	Alpha
Walking 100 mt	Item1	29508	0.829
Sitting 2 hours	Item2	29508	0.844
Getting up from chair	Item3	29508	0.831
Climbing several flights of stairs	Item4	29508	0.830
Climbing one flight of stairs	Item5	29508	0.830
Kneeling, crouching	Item6	29508	0.831
Extend arms above shoulder	Item7	29508	0.838
Pulling or pushing large objects	Item8	29508	0.827
Lifting or carrying weights over 5 kilos	Item9	29508	0.828
Picking up a coin from a table	Item10	29508	0.849
Test scale			0.848

Note: Cronbach's alpha is acceptable

Table 10A: Rotate factor loadings and unique variances of Casp items

		Factor 1	Factor 2	Factor 3	Uniqueness
Control	Age_prevents		0.77		0.39
	Out_control		0.76		0.36
	Left_out		0.64		0.46
Autonomy	Do_things	0.46	0.34		0.65
	Fam_responsib			0.81	0.32
	Money_shortage			0.54	0.61
Self-realisation	Energy	0.63	0.48		0.35
	Future_opportunities	0.72	0.33		0.37
	Good_future	0.73	0.33		0.36
Pleasure	Look_forward	0.67			0.53
	Life_meaning	0.76			0.40
	Happiness	0.67			0.49

Note: Instead of a 4-factor structure, three Factors are obtained. Sexton et al (2013) suggest to include only the items related to self-realisation and pleasure

Table 11A: Rotate factor loadings and unique variances of "hedonic" QoL

		Factor 1	Uniqueness
Self-realisation	Energy	0.77	0.41
	Future_opportunities	0.81	0.35
	Good_future	0.81	0.34
Pleasure	Look_forward	0.61	0.63
	Life_meaning	0.76	0.43
	Happiness	0.63	0.60

Note: The items load of one factor

Table 12A: Cronbach's alpha for hedonic Quality of Life

	Obs	**Alpha**
Energy	28694	0.789
Future_opportunities	28409	0.776
Good_future	28262	0.773
Look_forward	28538	0.823
Life_meaning	28420	0.791
Happiness	28575	0.817
Test scale		0.824

Note: Cronbach's alpha is acceptable

Table 13A: Rotated factor loadings and unique variances of Cognition items

	WAVE 5			**WAVE 6**		
	Factor 1	**Factor 2**	**Uniqueness**	**Factor 1**	**Factor 2**	**Uniqueness**
Reading_self		0.93	0.12		0.92	0.13
Writing_self		0.92	0.12		0.92	0.12
Memory_test	0.34	0.41	0.72		0.50	0.71
Orientation	0.32		0.84	0.59		0.66
Sub_numeracy	0.57	0.35	0.56	0.59	0.32	0.55
Immediate_recall	0.85		0.24	0.83		0.27
Delayed_recall	0.84		0.28	0.81		0.31
Verbal_fluency	0.69		0.45	0.68		0.46

Table 14A: Rotate factor loadings and unique variances of Physical items

		WAVE 5		WAVE 6	
Difficulties in:		Factor 1	Uniqueness	Factor 1	Uniqueness
Walking 100 mt	Item1	0.72	0.48	0.72	0.48
Sitting 2 hours	Item2	0.55	0.70	0.55	0.70
Getting up from chair	Item3	0.70	0.51	0.68	0.53
Climbing several flights of stairs	Item4	0.71	0.49	0.71	0.50
Climbing one flight of stairs	Item5	0.74	0.45	0.72	0.48
Kneeling, crouching	Item6	0.69	0.53	0.69	0.52
Extend arms above shoulder	Item7	0.62	0.61	0.61	0.62
Pulling or pushing large objects	Item8	0.74	0.45	0.73	0.46
Lifting or carrying weights over 5 kilos	Item9	0.73	0.46	0.73	0.47
Picking up a coin from a table	Item10	0.47	0.78	0.47	0.78

Table 15A: Rotate factor loadings and unique variances of "hedonic" QoL

		WAVE 5		WAVE 6	
		Factor 1	Uniqueness	Factor 1	Uniqueness
Self-realisation	Energy	0.76	0.43	0.75	0.44
	Future_opportunities	0.81	0.35	0.79	0.37
	Good_future	0.81	0.34	0.81	0.35
Pleasure	Look_forward	0.60	0.64	0.71	0.50
	Life_meaning	0.76	0.43	0.77	0.40
	Happiness	0.61	0.63	0.61	0.62

Table 16A: Table showing Cronbach's alpha and rho for each latent construct

Cronbach's alpha for Cognition	**WAVE 5**		**WAVE 6**	
	Obs	**Alpha**	**Obs**	**Alpha**
Orientation	35848	**0.802**	38231	**0.801**
Sub_numeracy	35539	0.730	37502	0.759
Immediate_recall	34980	0.668	37252	0.697
Delayed_recall	34865	0.691	37249	0.710
Verbal_fluency	34815	0.716	37297	0.744
Test scale		0.767		0.785
Cronbach's alpha for Physical	**WAVE 5**		**WAVE 6**	
	Obs	**Alpha**	**Obs**	**Alpha**
Walking 100 mt	36268	0.844	39735	0.839
Sitting 2 hours	36268	0.858	39735	0.853
Getting up from chair	36268	0.846	39735	0.841
Climbing several flights of stairs	36268	0.846	39735	0.841
Climbing one flight of stairs	36268	0.842	39735	0.839
Kneeling, crouching	36268	0.848	39735	0.842
Extend arms above shoulder	36268	0.852	39735	0.848
Pulling or pushing large objects	36268	0.843	39735	0.838
Lifting or carrying weights over 5 kilos	36268	0.844	39735	0.838
Picking up a coin from a table	36268	0.864	39735	0.859
Test scale		0.862		0.857
Cronbach's alpha for hedonic QoL	**WAVE 5**		**WAVE 6**	
	Obs	**Alpha**	**Obs**	**Alpha**
Energy	35137	0.783	37522	0.807
Future_opportunities	34659	0.769	37306	0.795
Good_future	34484	0.765	37141	0.791
Look_forward	34916	0.818	37403	0.817
Life_meaning	34801	0.784	37294	0.803
Happiness	34956	0.813	37420	0.834
Test scale		0.818		0.835

Table 17A: Rotated factor loadings and unique variances of Cognition items

	SUBGROUP A			SUBGROUP B		
	Factor 1	**Factor 2**	**Uniqueness**	**Factor 1**	**Factor 2**	**Uniqueness**
Reading_self		0.92	0.13		0.92	0.13
Writing_self		0.91	0.13		0.92	0.13
Memory_test		0.54	0.64		0.53	0.64
Orientation	0.40		0.78	0.38		0.80
Sub_numeracy	0.60	0.32	0.54	0.59		0.56
Immediate_recall	0.85		0.25	0.84		0.25
Delayed_recall	0.83		0.28	0.83		0.28
Verbal_fluency	0.67		0.46	0.67		0.48

Table 18A: Rotate factor loadings and unique variances of Physical items

		SUBGROUP A		SUBGROUP B	
Difficulties in:		Factor 1	Uniqueness	Factor 1	Uniqueness
Walking 100 mt	Item1	0.70	0.51	0.70	0.51
Sitting 2 hours	Item2	0.52	0.73	0.53	0.72
Getting up from chair	Item3	0.67	0.55	0.68	0.54
Climbing several flights of stairs	Item4	0.70	0.51	0.70	0.52
Climbing one flight of stairs	Item5	0.70	0.51	0.70	0.52
Kneeling, crouching	Item6	0.68	0.54	0.68	0.53
Extend arms above shoulder	Item7	0.61	0.63	0.59	0.65
Pulling or pushing large objects	Item8	0.73	0.47	0.72	0.48
Lifting or carrying weights over 5 kilos	Item9	0.72	0.48	0.72	0.48
Picking up a coin from a table	Item10	0.46	0.79	0.47	0.78

Table 19A : Rotate factor loadings and unique variances of "hedonic" QoL

		SUBGROUP A		SUBGROUP B	
		Factor 1	Uniqueness	Factor 1	Uniqueness
Self-realisation	Energy	0.77	0.41	0.76	0.42
	Future_opportunities	0.81	0.35	0.80	0.36
	Good_future	0.82	0.33	0.81	0.34
Pleasure	Look_forward	0.61	0.62	0.61	0.63
	Life_meaning	0.76	0.43	0.75	0.43
	Happiness	0.64	0.60	0.62	0.61

Table 20A: reliability index subgroups in overall WAVE 4

Cognition	**SUBGROUP A**		**SUBGROUP B**	
Cronbach's alpha	**Obs**	**Alpha**	**Obs**	**Alpha**
Orientation	14578	**0.803**	14594	**0.796**
Sub_numeracy	14766	0.738	14761	0.732
Immediate_recall	14337	0.683	14337	0.672
Delayed_recall	14329	0.703	14332	0.689
Verbal_fluency	14249	0.732	14252	0.725
Test scale		0.776		0.768
Reliability index rho	0.66		0.64	
Physical status	**SUBGROUP A**		**SUBGROUP B**	
Cronbach's alpha	**Obs**	**Alpha**	**Obs**	**Alpha**
Walking 100 mt	14758	0.829	14750	0.829
Sitting 2 hours	14758	0.844	14750	0.844
Getting up from chair	14758	0.831	14750	0.831
Climbing several flights of stairs	14758	0.830	14750	0.830
Climbing one flight of stairs	14758	0.829	14750	0.830
Kneeling, crouching	14758	0.832	14750	0.831
Extend arms above shoulder	14758	0.837	14750	0.839
Pulling or pushing large objects	14758	0.826	14750	0.827
Lifting or carrying weights over 5 kilos	14758	0.828	14750	0.828
Picking up a coin from a table	14758	0.849	14750	0.849
Test scale		0.848		0.848
Reliability index rho	0.86		0.86	
hedonic QoL	**SUBGROUP A**		**SUBGROUP B**	
Cronbach's alpha	**Obs**	**Alpha**	**Obs**	**Alpha**
Energy	14352	0.792	14342	0.785
Future_opportunities	14209	0.780	14200	0.773
Good_future	14110	0.777	14152	0.770
Look_forward	14279	0.826	14259	0.820
Life_meaning	14215	0.795	14205	0.787
Happiness	14297	0.819	14278	0.814
Test scale		0.827		0.821
Reliability index rho	0.84		0.83	

Table 21A: Goodness-of-fit statistics for overall measurement model of group A and group B

Fit statistics	**Cut-off value**	**Group A**	**Group B**
Chi-square	P>0.001	P<0.001	P<0.001
RMSEA	<0.08	0.051	0.049
CFI	>0.9	0.933	0.936
SRMR	<0.1	0.043	0.041

Table 22A: Rotated factor loadings and unique variances of Cognition items

	WAVE5_ONLY			WAVE6_ONLY		
	Factor 1	**Factor 2**	**Uniqueness**	**Factor 1**	**Factor 2**	**Uniqueness**
Reading_self		0.91	0.14		0.90	0.15
Writing_self		0.91	0.13		0.91	0.14
Memory_test		0.53	0.64		0.62	0.60
Orientation	0.40		0.78	0.49		0.73
Sub_numeracy	0.56	0.35	0.56	0.55	0.33	0.58
Immediate_recall	0.85		0.24	0.84		0.25
Delayed_recall	0.84		0.28	0.82		0.29
Verbal_fluency	0.66	0.31	0.47	0.64		0.52

Table 23A: Rotate factor loadings and unique variances of Physical items

		WAVE5_ONLY		WAVE6_ONLY	
Difficulties in:		Factor 1	Uniqueness	Factor 1	Uniqueness
Walking 100 mt	Item1	0.71	0.49	0.71	0.49
Sitting 2 hours	Item2	0.54	0.71	0.57	0.67
Getting up from chair	Item3	0.69	0.52	0.68	0.54
Climbing several flights of stairs	Item4	0.72	0.48	0.68	0.54
Climbing one flight of stairs	Item5	0.75	0.44	0.70	0.52
Kneeling, crouching	Item6	0.68	0.54	0.69	0.52
Extend arms above shoulder	Item7	0.62	0.61	0.60	0.64
Pulling or pushing large objects	Item8	0.73	0.46	0.71	0.50
Lifting or carrying weights over 5 kilos	Item9	0.73	0.47	0.70	0.50
Picking up a coin from a table	Item10	0.44	0.80	0.44	0.80

Table 24A: Rotate factor loadings and unique variances of "hedonic" QoL

		WAVE5_ONLY		WAVE6_ONLY	
		Factor 1	Uniqueness	Factor 1	Uniqueness
Self-realisation	Energy	0.76	0.42	0.77	0.41
	Future_opportunities	0.80	0.36	0.81	0.35
	Good_future	0.81	0.34	0.82	0.33
Pleasure	Look_forward	0.59	0.65	0.70	0.51
	Life_meaning	0.75	0.43	0.79	0.37
	Happiness	0.62	0.61	0.60	0.64

Table 25A: reliability index all individuals by WAVE5_ONLY & WAVE6_ONLY

Cognition	**WAVE5_ONLY**		**WAVE6_ONLY**	
Cronbach's alpha	**Obs**	**Alpha**	**Obs**	**Alpha**
Orientation	16001	**0.799**	10837	**0.789**
Sub_numeracy	15889	0.744	10581	0.741
Immediate_recall	15638	0.680	10527	0.671
Delayed_recall	15586	0.704	10521	0.686
Verbal_fluency	15540	0.730	10535	0.733
Test scale		0.775		0.769
Reliability index rho	0.64		0.61	
Physical status	**WAVE5_ONLY**		**WAVE6_ONLY**	
Cronbach's alpha	**Obs**	**Alpha**	**Obs**	**Alpha**
Walking 100 mt	16230	0.840	11154	0.828
Sitting 2 hours	16230	0.855	11154	0.840
Getting up from chair	16230	0.842	11154	0.831
Climbing several flights of stairs	16230	0.841	11154	0.832
Climbing one flight of stairs	16230	0.838	11154	0.830
Kneeling, crouching	16230	0.844	11154	0.830
Extend arms above shoulder	16230	0.848	11154	0.838
Pulling or pushing large objects	16230	0.839	11154	0.829
Lifting or carrying weights over 5 kilos	16230	0.839	11154	0.829
Picking up a coin from a table	16230	0.862	11154	0.851
Test scale		0.858		0.848
Reliability index rho	0.87		0.86	
hedonic QoL	**WAVE5_ONLY**		**WAVE6_ONLY**	
Cronbach's alpha	**Obs**	**Alpha**	**Obs**	**Alpha**
Energy	15674	0.779	10599	0.815
Future_opportunities	15426	0.767	10555	0.804
Good_future	15316	0.763	10535	0.802
Look_forward	15555	0.817	10569	0.830
Life_meaning	15530	0.781	10567	0.811
Happiness	15583	0.808	10578	0.847
Test scale		0.816		0.845
Reliability index rho	0.83		0.85	

Table 26A: Goodness-of-fit statistics for overall measurement model of wave5_only and wave6_only

Fit statistics	**Cut-off value**	**WAVE5_ONLY**	**WAVE6_ONLY**
Chi-square	P>0.001	P<0.001	P<0.001
RMSEA	<0.08	0.052	0.057
CFI	>0.9	0.930	0.919
SRMR	<0.1	0.044	0.052

Table 1B Standardized results of main analysis using FIML

	WAVE 4 Structural equation models Standard regression with composite variables				WAVE 5 Structural equation models Standard regression with composite variables				WAVE 6 Structural equation models Standard regression with composite variables			
	Model 1	Model 2	Model 3	Country FE	Model 1	Model 2	Model 3	Country FE	Model 1	Model 2	Model 3	Country FE
Cognition	**0.213**	**0.169**	**0.153**	**0.121**	**0.202**	**0.139**	**0.105**	**0.089**	**0.234**	**0.164**	**0.124**	**0.124**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical	**0.335**	**0.313**	**0.307**	**0.274**	**0.337**	**0.304**	**0.285**	**0.282**	**0.308**	**0.278**	**0.259**	**0.251**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female		**0.028**	**0.030**	**0.039**		**0.052**	**0.061**	**0.062**		**0.049**	**0.056**	**0.046**
		(0.003)	(0.001)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Education		**0.020**	0.013	**0.032**		**0.021**	-0.002	**0.021**		**0.031**	0.003	0.007
		(0.040)	(0.176)	(0.002)		(0.015)	(0.847)	(0.020)		(0.000)	(0.723)	(0.409)
Age		-0.010	-0.009	**-0.046**		-0.013	-0.012	**-0.034**		**-0.027**	**-0.029**	**-0.048**
		(0.301)	(0.377)	(0.000)		(0.131)	(0.170)	(0.000)		(0.002)	(0.000)	(0.000)
Married		**0.054**	**0.048**	**0.037**		**0.082**	**0.067**	**0.056**		**0.072**	**0.054**	**0.059**
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Household size		**-0.039**	**-0.035**	0.011		**-0.020**	**0.040**	**0.039**		**-0.022**	**0.046**	**0.020**
		(0.000)	(0.001)	(0.267)		(0.031)	(0.000)	(0.000)		(0.009)	(0.000)	(0.021)
Urban		**-0.037**	**-0.037**	-0.008		-0.001	**-0.017**	-0.008		**-0.036**	**-0.047**	0.003
		(0.000)	(0.000)	(0.365)		(0.907)	(0.034)	(0.279)		(0.000)	(0.000)	(0.717)
Social activities		**0.154**	**0.140**	**0.079**		**0.192**	**0.146**	**0.101**		**0.186**	**0.138**	**0.106**
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Income			**0.022**	**0.035**			**0.199**	**0.078**			**0.208**	**0.072**
			(0.031)	(0.005)			(0.000)	(0.000)			(0.000)	(0.000)
Assets			**0.087**	**0.038**			**0.063**	**0.045**			**0.062**	**0.029**
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.001)
Var(e.QoL)	0.810	0.781	0.774	0.675	0.811	0.768	0.728	0.677	0.819	0.777	0.735	0.672
N()	N(14,066)	N(14,066)	N(14,066)	N(14,066)	N(17,678)	N(17,678)	N(17,678)	N(17,678)	N(19,284)	N(19,284)	N(19,284)	N(19,284)
Chi-squared	P<0.001	P<0.001	P<0.001	P<0.001	P<0.001	P<0.001	P<0.001	P<0.001	P<0.001	P<0.001	P<0.001	P<0.001
RMSEA	0.046	0.040	0.039	0.043	0.048	0.042	0.040	0.044	0.049	0.042	0.040	0.038
CFI	0.922	0.909	0.905	0.819	0.917	0.905	0.903	0.822	0.915	0.903	0.901	0.849
TLI	0.911	0.895	0.891	0.789	0.906	0.890	0.887	0.792	0.903	0.888	0.886	0.824

Note: p-values in brackets

Table 2B Standardized results of main analysis using VCE(ROBUST)

	WAVE 4				WAVE 5				WAVE 6			
	Structural equation models				**Structural equation models**				**Structural equation models**			
	Standard regression with composite variables				Standard regression with composite variables				Standard regression with composite variables			
	Model 1	Model 2	Model 3	Country FE	Model 1	Model 2	Model 3	Country FE	Model 1	Model 2	Model 3	Country FE
Cognition	**0.213**	**0.170**	**0.162**	**0.124**	**0.199**	**0.134**	**0.105**	**0.088**	**0.233**	**0.160**	**0.116**	**0.118**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical	**0.334**	**0.309**	**0.299**	**0.269**	**0.333**	**0.304**	**0.282**	**0.276**	**0.306**	**0.283**	**0.259**	**0.249**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female		**0.023**	0.013	**0.029**		**0.043**	**0.044**	**0.045**		**0.048**	**0.057**	**0.046**
		(0.023)	(0.290)	(0.011)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Education		**0.025**	0.015	**0.035**		**0.027**	0.004	0.016		**0.030**	-0.003	-0.003
		(0.010)	(0.206)	(0.005)		(0.002)	(0.668)	(0.147)		(0.000)	(0.776)	(0.788)
Age		-0.009	-0.011	**-0.037**		-0.012	-0.001	-0.019		**-0.032**	**-0.023**	**-0.032**
		(0.404)	(0.395)	(0.003)		(0.229)	(0.927)	(0.101)		(0.001)	(0.030)	(0.002)
Married		**0.054**	**0.047**	**0.038**		**0.073**	**0.067**	**0.049**		**0.072**	**0.059**	**0.061**
		(0.000)	(0.001)	(0.003)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Household size		**-0.045**	**-0.032**	0.015		**-0.019**	**0.027**	**0.039**		**-0.027**	**0.033**	0.010
		(0.000)	(0.012)	(0.244)		(0.058)	(0.033)	(0.002)		(0.006)	(0.007)	(0.409)
Urban		**-0.036**	**-0.046**	**-0.024**		-0.003	-0.015	-0.011		**-0.037**	**-0.051**	-0.006
		(0.000)	(0.000)	(0.030)		(0.753)	(0.111)	(0.236)		(0.000)	(0.000)	(0.502)
Social activities		**0.154**	**0.139**	**0.076**		**0.194**	**0.169**	**0.114**		**0.183**	**0.150**	**0.115**
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Income			0.005	**0.031**			**0.196**	**0.068**			**0.206**	**0.069**
			(0.695)	(0.034)			(0.000)	(0.000)			(0.000)	(0.000)
Assets			**0.089**	**0.033**			**0.071**	**0.049**			**0.074**	**0.038**
			(0.000)	(0.002)			(0.000)	(0.000)			(0.000)	(0.000)
Var(e.QoL)	0.811	0.784	0.779	0.675	0.817	0.773	0.718	0.660	0.822	0.776	0.730	0.660
N()	N(13,568)	N(12,464)	N(8,814)	N(8,814)	N(16,927)	N(15,668)	N(10,871)	N(10,871)	N(18,790)	N(17,382)	N(12,371)	N(12,371)
SRMR	0.041	0.035	0.034	0.031	0.042	0.035	0.035	0.033	0.042	0.035	0.034	0.027
CD	0.965	0.965	0.965	0.969	0.967	0.967	0.970	0.972	0.967	0.968	0.970	0.972

Note: p-value in brackets

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