An examination of the heterogeneity in the pattern and association between rates of change in grip strength and global cognition in late life. A multivariate growth mixture modelling approach

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Abstract

Background: previous research has demonstrated how older adults exhibit different patterns of change in cognitive and physical functioning, suggesting differences in the underlying causal processes.

Objective: to (i) identify subgroups of older adults that best account for different patterns of longitudinal change in performance on global cognition and grip strength, (ii) examine the interrelationship between global cognition and grip strength trajectories within these subgroups and (iii) identify demographic and health-related markers of class membership.

Methods: multivariate growth mixture models (GMM) were used to identify groups of individuals with similar developmental trajectories of muscle strength measured by grip strength, and global cognition measured by Mini Mental State Examination (MMSE).

Results: GMM analyses indicated high, moderate and low functioning groups. Individuals in the high and moderate classes demonstrated better cognitive and physical functioning at the start of the study and less decline than those in the low functioning group. Notably, cognitive performance was related to physical functioning at study entry only among individuals in the low functioning group.

Conclusion: the study demonstrates the applicability of the multivariate GMM to achieve a better understanding of the heterogeneity of various aging related processes.

Keywords: longitudinal analysis, trajectories, growth mixture model, cognition, grip strength, older people

Introduction

Current aging research is largely focused on better understanding underlying aging processes with the aim to promote healthy aging. Over the past few decades, the aging of physical and cognitive processes has received extensive attention and has been found to be associated with overall health and

increased risk of morbidity, mortality and dementia [1, 2]. Still, a greater focus on the individual differences in patterns and causes of changes in physical and cognitive processes over the life course is needed for predicting late life outcomes and for developing interventions to reduce the risk of negative health outcomes.

Although there is consensus that cognitive performance generally declines with age, some evidence suggests that this decline is not normative [3–5]. Similarly, longitudinal studies demonstrate physical decline with age [6]. Despite these similar findings, few, if any, studies have examined the interindividual heterogeneity and the interrelationships in these trajectories.

Developments in the analysis of longitudinal data have resulted in recent studies focused on better understanding heterogeneity in the trajectories of cognitive functioning. One such development, referred to as growth mixture models (GMM), allows for the identification of different classes of individuals who cluster together, thus identifying more than one trajectory within the population [7–9]. GMM provides information about the optimal number of classes and the characteristics of each class, including the mean intercept and slope, proportion of membership, and significant predictors of class membership.

When GMM [e.g. 7, 8] have been used to explore various patterns of cognitive aging [3–5, 10, 11], they have typically suggested two (slow and rapid decliners) [10, 11] or three (low, moderate and rapid decliners) [3, 4] classes that best represent the underlying heterogeneity of cognitive trajectories.

Most analyses of the association between cognitive and physical functioning have been based on modelling approaches (e.g. multivariate growth curve model) not taking into account the possibility for different clusters of individuals exhibiting distinct patterns of change and cross-domain interrelationships. It is quite strongly supported that cognitive and physical functioning are related in cross-sectional studies, and more weakly in longitudinal analyses [12]. How these two processes are interrelated, however, is largely unknown. More studies are needed that explore the relationship between physical and cognitive functioning within different classes of trajectories. Using a GMM with multiple outcomes (i.e. multivariate GMM) allows the exploration of not only the different classes of cognitive and physical functioning but also the association between the two outcomes within each of the identified classes.

The purpose of this study was to (i) identify subgroups of older adults best describing longitudinal change in performance on the Mini Mental State Examination (MMSE) and grip strength, (ii) examine the associations between MMSE and grip strength trajectories within each subgroup and (iii)

evaluate the role of cognitive and physical activity and demographic variables on differences in class membership.

Grip strength was chosen as a biomarker of physical functioning given its sensitivity to physiological change [13] and its use as a valid marker of frailty [14]. Its simplicity to administer, portability and affordability make it easy to apply in numerous settings [13]. The MMSE was selected as the cognitive measure given that a systematic review by Clouston and colleagues [12] found that the MMSE was more strongly related with grip strength than domain-specific measures of cognition in older adults.

Method

Data

Origins of Variance in the Oldest-Old (OCTO-Twin)

The OCTO-Twin study included dizygotic and monozygotic twin pairs aged 80 years of age and older [15, 16]. The sample was selected from older adults in the population-based Swedish Twin Registry [17]. Five cycles of longitudinal data were collected at 2-year intervals. The full sample consisted of 702 individuals (351 same-sex pairs). Individuals were excluded due to missing data on the covariates. The sample used in the analysis consisted of 369 individuals ranging from 79.4 to 97.9 years of age. The rate of attrition ranged from 10.5% to 28.8% every two years, primarily due to death (see Table 1). Ethical approval for OCTO-Twin was obtained from the Ethics Committee at the Karolinska Institute in Stockholm and the Swedish Data Inspection Board. Informed consent was obtained from all participants. Descriptive statistics at each occasion for all variables are provided in Table 1.

Measures

MMSE

The MMSE, administered in Swedish, was used to assess global cognitive functioning at each measurement occasion [18].

Grip strength

A Martin vigorimeter (Elmed Inc., Addison, IL, USA; medium size bulb) to measure maximum force in pounds

Table 1. Descriptive statistics and attrition rate for MMSE and grip strength at each wave of data collection

Variables	Baseline	Time 2	Time 3	Time 4	Time 5
MMSE – mean (SD)	25.59 (4.8)	24.62 (6.7)	23.51 (7.9)	22.98 (8.4)	21.55 (8.7)
MMSE – N (%) [*]	367	299 (18.5)	229 (23.4)	168 (26.6)	120 (28.6)
Grip – mean (SD)	8.60 (3.0)	7.93 (2.9)	6.98 (3.1)	6.53 (3.0)	6.35 (2.9)
Grip – N (%) [*]	314	281 (10.5)	224 (20.3)	160 (28.6)	114 (28.8)
Males – N (%)	118 (32)				
Age – mean (SD)	82.9 (3.26)				
Edu – mean (SD)	7.28 (2.6)				
Height – mean (SD)	161.21(9.1)				

Note. N = 369. ^{*}Sample size at each data wave and attrition rate every 2 years. Edu = years of education. Height in cm.

per square inch was used [19]. Participants performed the task three times per hand, with the final score being the maximum force exerted.

Covariates

Age, education and sex were included as covariates on the intercept and slope, and as markers of class membership. Height, level of physical activity, and engagement in cognitive activities were included as markers of class membership. Age, education and height were centred at their mean value. Sex was coded as 0 for males and 1 for females. Level of physical activity was measured by asking respondents: 'Are you presently doing or have you previously done anything special to train your body or 'keep your body fit'?'. Response options were 'no', 'yes, to some extent' or 'yes, to a great extent'. These were used to derive an indicator as sedentary (0) and active (1). The cognitive activity measure was created by summing six items (e.g. playing games) dichotomously as 'no' (0) or 'yes' (1) and one item about training the memory and keeping the mind active as 'no' (0), 'yes, to a certain degree' (1), or 'yes, definitely' (2). Total scores ranged from 0 to 8 with higher scores signifying higher engagement in cognitive activity.

Analysis

Multivariate GMM [20] were employed to identify unobserved groups of individuals with similar linear developmental bivariate trajectories of grip strength and MMSE scores. Class membership was estimated using a multinomial logistic regression adjusted for the covariates. GMM provide estimates of the average MMSE and grip strength trajectories (intercept and slope) and variation for older adults in each latent class [8, 9, 21]. The number of classes is unknown a priori, therefore, we followed recommended

procedures to select the best fitting model. First, models were fitted with increasing number of classes. To determine the optimal number of classes, Bayesian Information Criterion (BIC) values were compared from each model. Models with lower BIC values were considered better fitting [22]. Classification quality using entropy values (range from 0 to 1 with higher values meaning that individuals are better discriminated between classes) [23] and interpretability of classes was further considered.

Mplus version 7.2 was used to run the GMMs [24]. The model was estimated by maximum likelihood with robust standard errors. Missing data were assumed to be missing at random.

Results

Number of classes

A three-class model of cognitive and physical functioning was selected, given its lower BIC values (2 class = 18,411.00; 3 class = 18,254.08) and good classification of individuals in each class (entropy 2 class = 0.85; entropy 3 class = 0.81). Parameter estimates and standard errors for the three-class model are presented in Table 2.

Grip strength and MMSE trajectories

Class 1: The largest class was composed of 147 individuals (40% of sample) with good physical and cognitive functioning and slow decline. In this high functioning group, individuals had an average baseline MMSE score of 28.62 (SE = 0.17) and declined at a rate of 0.12 (SE = 0.048). See upper solid line in Figure 1. The average baseline grip strength score was 11.49 kPa (SE = 0.48) and rate of decline was 0.37 kPa (SE = 0.077) per year. See lower solid line in Figure 1. No associations were found between grip strength and MMSE. See intercept–intercept and slope–slope covariances in Table 2.

Table 2. Estimates and standard errors for the three-class growth mixture model of cognitive and physical functioning

	Class 1 (N = 147)		Class 2 (N = 114)		Class 3 (N = 108)	
	MMSE	Grip Strength	MMSE	Grip Strength	MMSE	Grip strength
	Estimates (SE)	Estimates (SE)	Estimates (SE)	Estimates (SE)	Estimates (SE)	Estimates (SE)
Fixed effects						
Intercept	28.62 (0.17)***	11.49 (0.48)***	26.84 (1.08)***	10.54 (0.49)***	23.71 (1.24)***	8.46 (0.82)***
Age	−0.09 (0.06)	−0.12 (0.08)	−0.34 (0.13)*	−0.30 (0.12)*	−0.18 (0.22)	−0.18 (0.13)
Education	0.04 (0.05)	0.01 (0.09)	0.15 (0.25)	−0.008 (0.14)	0.96 (0.41)*	0.10 (0.22)
Sex	0.08 (0.94)	−3.02 (0.59)***	0.39 (1.37)	−2.93 (0.70)***	−2.90 (1.98)	−1.48 (0.96)
Slope	−0.12 (0.05)*	−0.37 (0.08)***	−0.66 (0.19)**	−0.57 (0.06)***	−2.10 (0.18)***	−0.84 (0.12)***
Age	−0.003 (0.02)	−0.007 (0.03)	−0.03 (0.06)	0.003 (0.02)	0.09 (0.03)	0.04 (0.02)
Education	0.01 (0.04)	−0.003 (0.03)	0.06 (0.10)	−0.02 (0.04)	−0.04 (0.24)	−0.05 (0.03)
Sex	0.07 (0.09)	0.10 (0.09)	−0.23 (0.55)	0.16 (0.11)	−0.29 (0.37)	0.005 (0.36)
Random effects						
Intercept	0.41 (1.67)	3.90 (0.59)***	0.41 (1.67)	3.90 (0.59)	0.41 (1.67)	3.90 (0.59)***
Slope	0.04 (0.02)	0.009 (0.009)	0.04 (0.02)	0.009 (0.009)	0.04 (0.02)	0.009 (0.009)
Covariance						
Intercept–Intercept	0.04 (0.38)		−0.30 (0.80)		4.89 (0.81)***	
Slope–Slope	0.003 (0.02)		0.002 (0.03)		0.01 (0.02)	

Note. N = 369. SE = standard errors. Class 1 = high functioning group. Class 2 = moderate functioning group. Class 3 = low functioning group.

Figure 1. Average trajectories of physical and cognitive functioning for the three classes. The three upper lines represent cognitive functioning and the three lower lines physical functioning. The solid lines represent high functioning individuals, the dotted lines represent moderate functioning individuals, and the dotdash lines represent low functioning individuals.

Class 2: A class of 114 individuals (31% of sample) with slightly lower average baseline scores and steeper declining MMSE scores and grip strength was identified. In this moderate functioning group, the average baseline MMSE score was 26.84 (SE = 1.08) and average rate of decline was 0.66 (SE = 0.19). See upper dotted line in Figure 1. Average baseline grip strength was 10.54 kPa (SE = 0.49) and decline rate was 0.57 kPa (SD = 0.064). See lower dotted line in Figure 1. No associations were found between grip strength and MMSE. See intercept–intercept and slope–slope covariances in Table 2.

Class 3: A low functioning group, composed of 108 individuals (29% of sample), demonstrated lower MMSE scores and weaker grip strength at the start of the study and steeper rate of decline compared to those in the other two classes. These individuals had an average baseline MMSE score of 23.71 (SE = 1.24) and decline rate of 2.10 kPa (SE = 0.18) per year (see upper dotdash line in Figure 1); and a baseline grip strength score of 8.46 kPa (SE = 0.82) and decline rate of 0.84 kPa (SE = 0.12) per year (see lower dotdash line in Figure 1). Individuals with stronger grip strength at the start of the study also demonstrated higher MMSE scores. No relationship was found between the rate of change in grip strength and the rate of change in MMSE. See intercept–intercept and slope–slope covariances in Table 2.

Covariates

In the high functioning group (class 1), none of the covariates were associated with MMSE at study entry. Sex was associated with baseline grip strength, with females having lower grip strength scores. In the moderate functioning

group (class 2), individuals who were older in age at baseline had lower MMSE scores. Female participants and individuals who were older had lower grip strength. In the low functioning group (class 3), individuals with higher educational attainment had higher baseline MMSE scores.

Markers of class membership

Participation in physical and cognitive activities was markers of class membership. Membership in class 2 was associated with engagement in physical activities (Estimate = 1.31*; SE = 0.53). Individuals who were engaged in physical activities had higher probability of being in the moderate functioning group compared to the low functioning group (class 3) than individuals who did not participate in physical activity. Membership in class 1 was associated with engagement in cognitive activities (Estimate = 0.68***; SE = 0.18). Individuals who reported higher levels of engagement in cognitive activities had a higher probability of being in the high functioning group compared to the low functioning group than individuals who engaged in fewer cognitive activities. Class membership was not influenced by age, height, education or sex.

Discussion

Our findings demonstrate the use of GMM to examine clusters of trajectories based on MMSE and grip strength scores and for profiling the characteristics of individuals within clusters. This is very important as many research questions focus on the dynamic relationship between selected developmental processes and how they may change over time.

Our results show that age-related decline in physical and cognitive function was heterogeneous and not universal. We identified three distinct classes of trajectories for MMSE and grip strength in the oldest-old segment of the population. The high functioning group with good physical and cognitive performance showed minor decline and represents successful agers. The moderate functioning group who had lower cognitive and physical performance and steeper rate of decline than those in the high functioning group might be at greater risk of more substantial decline. On average, they entered the study with an MMSE score of 26.8 which is close to the cut-off score of 26 used to identify individuals at risk of mild cognitive impairment (MCI) and dementia [25]. The low functioning group, with the lowest cognitive and physical performance scores and steepest rate of decline, is likely those who are at greatest risk of also developing clinical dementia. Their average baseline score of 23.7 meets MCI criteria, [25] and almost meets the cut-off of 23 often used for clinical dementia [18].

Interestingly, we found no evidence for differences between the sexes in the low functioning group, suggesting that, for those individuals who are most frail, there are only minor or no differences between men and women. Our finding about the role of education suggests that less educated older adults in the low functioning group are at an increased risk of dementia and highlights the protective role of educational attainment in delaying the onset of the

disease which is in line with the cognitive reserve hypothesis [26]. The importance of specific covariates in different classes would have been masked had we examined only one trajectory class, highlighting the importance of GMM.

Participation in cognitive and physical activities was associated with an increased likelihood of being in the highly or moderately functioning group compared to the lower functioning group. This aligns with previous longitudinal research on the importance of physical and cognitive activity [27]. Unlike previous studies which focused on the importance of lifestyle activities on the intercept and rate of change (i.e. whether participation in activities can delay decline) of physical and cognitive functioning, the current study demonstrated that these activities increase the likelihood that an individual will follow the highly or moderately functioning trajectory over the course of their later life rather than following the poorly functioning trajectory. This finding suggests that it would be effective to implement interventions which entail increased participation in physical and cognitive activities.

By identifying subgroups of individuals with similar changes in cognitive and physical functioning, we were able to better understand the relationship between these two dimensions of the aging process. Our finding that individuals with higher cognitive scores at baseline also had higher grip strength in only one class (low functioning group) suggests that the relationship between the two processes may be most relevant for those individuals who are especially frail and cognitively impaired. The fact that we only found a relationship in one class may help explain previous mixed results about the association between cognitive and physical functioning as other modelling approaches tend to assume that individual trajectories follow a single pattern of change.

One limitation of this study is the use of the MMSE with its well-known ceiling effect and modest accuracy in identifying individuals with dementia [28]. Still, the MMSE is suitable for this study since it was not used as a diagnostic tool. Another limitation is that the sample size was too small to model the GMM separately for male and female participants knowing that older adults differ in grip strength norms [29]. Still, a recent bivariate study modelled both sexes together and found a relationship between grip strength and cognition [30].

To the best of our knowledge, this is the first study to examine the longitudinal relationship of subpopulations characterised by their physical and cognitive functioning trajectories. Our research demonstrates that cognitive and physical functioning is best described by more than one trajectory and that studies assuming a single population with an average developmental trajectory tend to miss important information about the class-specific relation between physical and cognitive functioning and class-specific markers. More research is needed to further identify risk factors to being in the low functioning group as these individuals might benefit the most from targeted interventions. Further research is also needed to examine whether similar subpopulations are found when including younger older adults and whether subpopulations of trajectories also exist for

other biopsychosocial aging processes. Rather than assuming that aging individuals all follow a similar pattern of change, GMM allows for the modelling of subpopulations of trajectories which can have important implications for better tailored interventions.

Key points

- Cognitive and physical functioning is best described by three distinct classes of trajectories.
 - This study demonstrates the applicability of the multivariate growth mixture model (GMM), decline in physical and cognitive function is heterogeneous and not normative.
 - Modelling subpopulations of trajectories is needed for better tailored interventions.
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Conflict of interest

None.

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References

1. Cooper R, Hardy R, Aihie Sayer A *et al.* Age and gender differences in physical capability levels from mid-life onwards: the harmonisation and meta-analysis of data from eight UK cohort studies. *PLoS One* 2011; 6: e27899. doi:10.1371/journal.pone.0027899.
2. Brown JC, Harhay MO, Harhay MN. Walking cadence and mortality among community-dwelling older adults. *J Gen Intern Med* 2014; 29: 1263–9.
3. Terrera GM, Brayne C, Matthews F. One size fits all? Why we need more sophisticated analytical methods in the explanation of trajectories of cognition in older age and their potential risk factors. *Int Psychogeriatr* 2010; 22: 291–9. doi: <http://dx.doi.org/10.1017/S1041610209990937>; PubMed PMID: 223742514; 19906326.
4. Hayden KM, Reed BR, Manly JJ *et al.* Cognitive decline in the elderly: an analysis of population heterogeneity. *Age Ageing* 2011; 40: 684–9.
5. Xie H, Mayo N, Koski L. Identifying and characterizing trajectories of cognitive change in older persons with mild cognitive impairment. *Dement Geriatr Cogn Disord* 2011; 31:

- 165–72. doi: <http://dx.doi.org/10.1159/000323568>; PubMed PMID: 859334228; 21346357.
6. Jerome GJ, Ko S-U, Kauffman D, Studenski SA, Ferrucci L, Simonsick EM. Gait characteristics associated with walking speed decline in older adults: results from the Baltimore longitudinal study of aging. *Arch Gerontol Geriatr* 2015; 60: 239–43. doi: [10.1016/j.archger.2015.01.007](https://doi.org/10.1016/j.archger.2015.01.007).
 7. Liu M, Hancock G. Unrestricted mixture models for class identification in growth mixture modeling. *Educ Psychol Meas* 2014; 74: 557–84. doi: [10.1177/0013164413519798](https://doi.org/10.1177/0013164413519798).
 8. Muthén B. Latent Variable Analysis: Growth Mixture Modeling and Related Techniques for Longitudinal Data. The SAGE Handbook of Quantitative Methodology for the Social Sciences. Thousand Oaks, CA: SAGE Publications, Inc, 2004; pp. 346–70.
 9. Muthén B, Shedden K. Finite mixture modeling with mixture outcomes using the EM algorithm. *Biometrics* 1999; 55: 463–9. doi: [10.1111/j.0006-341x.1999.00463.x](https://doi.org/10.1111/j.0006-341x.1999.00463.x).
 10. Proust C, Jacqmin-Gadda H. Estimation of linear mixed models with a mixture of distribution for the random effects. *Comput Methods Programs Biomed* 2005; 78: 165–73. doi: <http://dx.doi.org/10.1016/j.cmpb.2004.12.004>.
 11. Small BJ, Backman L. Longitudinal trajectories of cognitive change in preclinical Alzheimer's disease: a growth mixture modeling analysis. *Cortex* 2007; 43: 826–34. doi: [10.1016/S0010-9452\(08\)70682-8](https://doi.org/10.1016/S0010-9452(08)70682-8).
 12. Clouston SA, Brewster P, Kuh D *et al*. The dynamic relationship between physical function and cognition in longitudinal aging cohorts. *Epidemiol Rev* 2013; 35: 33–50. Epub 2013/01/26. doi: [10.1093/epirev/mxs004](https://doi.org/10.1093/epirev/mxs004); PubMed PMID: 23349427; PubMed Central PMCID: PMC3578448.
 13. Bohannon RW. Hand-grip dynamometry predicts future outcomes in aging adults. *J Geriatr Phys Ther* 2008; 31: 3–10. Epub 2008/05/21. PubMed PMID: 18489802.
 14. Syddall H, Cooper C, Martin F, Briggs R, Aihie Sayer A. Is grip strength a useful single marker of frailty? *Age Ageing* 2003; 32: 650–6. Epub 2003/11/06. PubMed PMID: 14600007.
 15. Johansson B, Hofer SM, Allaire JC *et al*. Change in memory and cognitive functioning in the oldest-old: The effects of proximity to death in genetically related individuals over a six-year period. *Psychol Aging* 2004; 19: 145–56.
 16. McClearn GE, Johansson B, Berg S *et al*. Substantial genetic influence on cognitive abilities in twins 80 or more years old. *Science* 1997; 276: 1560–3.
 17. Cederlöf R, Lorch U. The Swedish Twin Registry. In: Nance WE, Allen G, Parisi P, eds. *Twin research: Biology and epidemiology*. New York, NY: Alan R. Riss, 1978; pp. 189–95.
 18. Folstein MF, Folstein SE, McHugh PR. Mini-mental state': a practical method for grading the cognitive state of patients for the clinician. *J Psychiatr Res* 1975; 12: 189–98.
 19. Sipers WM, Verdijk LB, Sipers SJ, Schols JM, van Loon LJ. The Martin vigorimeter represents a reliable and more practical tool than the Jamar dynamometer to assess handgrip strength in the geriatric patient. *J Am Med Dir Assoc* 2016; 17: 466.e1–7. Epub 2016/04/24. doi: [10.1016/j.jamda.2016.02.026](https://doi.org/10.1016/j.jamda.2016.02.026); PubMed PMID: 27107163.
 20. Wu J, Witkiewitz K, McMahon RJ, Dodge KA. A parallel process growth mixture model of conduct problems and substance use with risky sexual behavior. *Drug Alcohol Depend* 2010; 111: 207–14. doi: <http://dx.doi.org/10.1016/j.drugalcdep.2010.04.013>; PubMed PMID: 2010-20916-004.
 21. Berlin KS, Parra GR, Williams NA. An introduction to latent variable mixture modeling (part 2): longitudinal latent class growth analysis and growth mixture models. *J Pediatr Psychol* 2014; 39: 188–203. doi: [10.1093/jpepsy/jst085](https://doi.org/10.1093/jpepsy/jst085).
 22. Nylund KL, Asparouhov T, Muthén BO. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. *Struct Equ Modeling* 2007; 14: 535–69. doi: [10.1080/10705510701575396](https://doi.org/10.1080/10705510701575396).
 23. Celeux G, Soromenho G. An entropy criterion for assessing the number of clusters in a mixture model. *J Classif* 1996; 13: 195–212. doi: [10.1007/BF01246098](https://doi.org/10.1007/BF01246098).
 24. Muthén LK, Muthén BO. *Mplus User's Guide*, 7th ed. Los Angeles, CA: Muthén & Muthén, 1998-2015.
 25. Nasreddine ZS, Phillips NA, Bédirian V *et al*. The Montreal Cognitive Assessment, MoCA: a brief screening tool for mild cognitive impairment. *J Am Geriatr Soc* 2005; 53: 695–9. doi: [10.1111/j.1532-5415.2005.53221.x](https://doi.org/10.1111/j.1532-5415.2005.53221.x).
 26. Terrera GM, Minett T, Brayne C, Matthews FE. Education associated with a delayed onset of terminal decline. *Age Ageing* 2014; 43: 26–31. doi: [10.1093/ageing/afu150](https://doi.org/10.1093/ageing/afu150); PubMed PMID: PMC3861340.
 27. Lindwall M, Cimino CR, Gibbons LE *et al*. Dynamic associations of change in physical activity and change in cognitive function: coordinated analyses of four longitudinal studies. *J Aging Res* 2012; 2012: 493598. doi: [10.1155/2012/493598](https://doi.org/10.1155/2012/493598).
 28. Mitchell AJ. A meta-analysis of the accuracy of the mini-mental state examination in the detection of dementia and mild cognitive impairment. *J Psychiatr Res* 2009; 43: 411–31. doi: <http://dx.doi.org/10.1016/j.jpsychires.2008.04.014>.
 29. Proctor DN, Fauth EB, Hoffman L *et al*. Longitudinal changes in physical functional performance among the oldest old: insight from a study of Swedish twins. *Aging Clin Exp Res* 2006; 18: 517–30. Epub 2007/01/27. PubMed PMID: 17255642.
 30. Björk MP, Johansson B, Hassing LB. I forgot when I lost my grip—strong associations between cognition and grip strength in level of performance and change across time in relation to impending death. *Neurobiol Aging* 2016; 38: 68–72. doi: [10.1016/j.neurobiolaging.2015.11.010](https://doi.org/10.1016/j.neurobiolaging.2015.11.010).

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