Journal of
Gerontology & Geriatric Research
ISSN: 2167-7182

Research Article OMICS International

Body Mass Index Is Related to Cognitive Function in Chinese Older Adults: So What?

Chongming Yang[1]*, Hui Hu[2], Ling Wang[2], Yating Ai[2], Hairong Ren[2], Xinxiu Dong[2], Fen Yang[2] and Yuncui Wang[2]

[1]*Brigham Young University, Provo, Utah, USA*
[2]*Hubei University of Chinese Medicine, No.1 West Huangjia Lake Road, Hong Shan District, Wuhan City, Hubei Province, China*

Abstract

The relation between Body Mass Index (BMI) and cognitive function in the elderly was found conflictory in studies of western samples and under-explored in mainland China. This study explored the relation with a sample of 447 older adults from Wuhan, central China. Cognitive function was measured with the Chinese version of Montreal Cognitive Assessment (MoCA). A mixture modeling revealed that BMI was negatively related to cognitive function only in a small proportion of the sample, who averaged highest in age but lowest in education and BMI. Practical implication of this finding was discussed.

Keywords: Body mass index; Montreal cognitive assessment (Moca); Mixture modeling

Introduction

Accumulating studies have explored the relation of body mass index (BMI) to cognitive function (CF) in elderly populations of western countries. Inconsistent relations, however, have been found between BMI and CF in the elderly [1]. Some studies found a negative relation [2-5]; others found a positive relation [6,7]; while some studies found no relations [8]. As for the negative relations, it is also noteworthy that lower BMI could lead to impaired CF [9,10]. In addition, the relation differed across ethnic groups [11], in that the negative relation was found in a white sample and an only overweight African American sample, but a positive relation was found in the Hispanic sample. With such conflictory findings, it was difficult to ascertain what the relation could be in mainland Chinese older adults, among whom the prevalence of impaired CF appears to be increasing [12].

In mainland China, studies that explored the relation of BMI to cognitive function were limited in number and complicated in their findings. One study found that odds of CF impairment were higher in overweight respondents compared to normal ones [13]. The other study did not find any mean differences in the cognitive function was measured with Mini Mental State Examination (MMSE) among different groups of waist-circumferences, although the conclusion was equivocal [14]. It was not clear to what extent that any of the patterns could be replicated with other samples from mainland China.

The inconsistent findings mentioned above might be ascribed to methodological variations and the true causal mechanism. Methodological variations in the aforementioned studies involved sampling (i.e., normative large samples vs. small clinical samples, cross-sectional vs. longitudinal), statistical treatment of BMI (i.e., continuous raw scores, categorized, or dummy-coded), measurement of cognitive functions (i.e., different CF scales), and inclusion of different covariates in models.

The causal mechanism of BMI to impaired CF has been implicitly or explicitly presumed in many studies, with high BMI as a risk factor of impaired CF [15]. However, a direct causality from high BMI to impaired CF has not been supported by genetic studies, as indicated by findings of seven common genetic variants for both traits and a large genetic correlation (r=-0.51); [16]. With such a strong genetic predisposition for both BMI and impaired CF, the relation of BMI to CF might have been misconceptualized as causal and thus difficult to be consistent in the findings. Instead, it might better be conceived as a comorbidity and the result of genes-environment interaction in a broader perspective. Therefore, the relation may be expected to be more observable in the overweight population, in whom both traits have manifested to various extents [8,17].

Low BMI in the other extreme could also be related to impaired CF. Some studies examined the nutritional status of elderly either in term of BMI or measures of nutrition and found that those with moderate or severe cognitive impairment also had higher risks of malnutrition [15,18-20] Although it was difficult to determine from these studies, there is good reason to consider that malnutrition caused cognitive impairment, as many nutritional elements are needed in biochemical processes [21].

Analytically, studies of the BMI-CF relations at the behavioral/psychological level might be more revealing, if participants of over- or under-weight are examined separately from normal ones, as has been referred to as the person-centered approach [22,23]. As opposed to a variable-centered approach that primarily examines the relations of variables, a person-centered approach identifies heterogeneous subgroups (also referred to as classes) and examines the variable relations in each subgroup, known as mixture modeling [24]. If variable relations differ across identified subgroups, complicated interactions exist among the covariates that predict the classes and the focal exogenous variable [25]. Thus, mixture modeling can reveal complicated interaction effects by identifying heterogeneous subsamples, which might display a relation of comorbid undesirable BMI and CF.

This study was thus aimed to explore the relation of BMI to CF in another Chinese sample drawn from Wuhan, a large city in central China. Given the common genetic basis for both BMI and CF, we hypothesized that the relation of BMI to CF would be identified only in a subgroup of the participants who might be in the high end of BMI and combinations of different levels of the covariates. This study differed from previous studies in China, in that we applied mixture modeling to the data to identify potential heterogeneous subsamples with potential

***Corresponding author:** Chongming Yang, Brigham Young University, Provo, Utah, USA, Tel: 801-422-4636; E-mail: chongming_yang@byu.edu

Received June 12, 2017; **Accepted** July 11, 2017; **Published** July 14, 2017

Citation: Yang C, Hu H, Wang L, Ai Y, Ren H, et al. (2017) Body Mass Index Is Related to Cognitive Function in Chinese Older Adults: So What? J Gerontol Geriatr Res 6: 437. doi:10.4172/2167-7182.1000437

Copyright: © 2017 Yang C, et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

different relations of BMI to MoCA. The proposed graphic model is depicted in Figure 1 below.

In the graphic model above, latent class in the oval is a categorical hypothetical variable that classifies the sample into different heterogeneous groups (classes). The covariates affect the latent class variable (the class membership) of the participants. CF is a latent variable measured with items of the Chinese Version of Montreal Cognitive Assessment (MoCA).

Materials and Methods

Participants

A total of 447 senior community residents participated in the study, with 39.6% male and 60.4% female. The participants were respectively aged 60-65 (30.2%), 65-69 (23.9%), 70-75 (19.2%), 76-80 (15.9%), and above 80 (10.7%). Education of the participants included "no schooling or below elementary school (11.4%), elementary school level (22.8%), middle school level (34.0%), high school or vocational school (24.8%), college and above (6.9%). In addition, 13.2% of the participants were living alone at the time of the data collection, while the other 86.8% were living with spouses or other family members. Before retirement, 35.3% of the participants were employed in the physical labor force, while the rest of the sample (64.7%) were mental-labor workers. Monthly incomes of the participants in Chinese currency were respectively below ¥1000 (3.6%), ¥1000-¥1999 (17.7%), ¥2000-¥2999 (56.4%), ¥3000-¥4000 (17.0%), and above ¥4000 (5.4%). About 32.0% participants reported to have one hobby, while 68.0% had two or more hobbies. About two-thirds (66.4%) of the participants reported a history of a certain disease (i.e., renal or hepatic insufficiency, drug abuse, or unspecified), while 33.6% of the participants reported no history of any disease.

Sampling

Stratified sampling was adopted for this study. First, three districts were selected out of 13 districts of Wuhan City. Second, 13 communities within the three districts were selected to respectively represent central urban, urban fringe, and suburban communities. Participants in this study were screened out from these communities to meet the following criteria: (1) age ≥ 60; (2) having sufficient vision and hearing for neural and mental tests; (3) being willing to be assessed in CF and biomedical conditions; (4) without CF impairment caused by serious heart, liver, kidney, or other diseases.

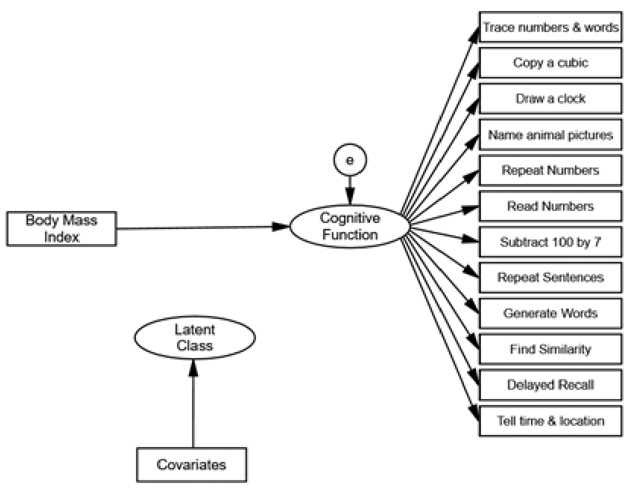

Figure 1: Profiles of three classes.

Measurement

Cognitive function was measured with the Beijing Chinese version of Montreal cognitive assessment [26]. The culturization of MoCA is mainly a substitution of English letters and words with Chinese words.

BMI was calculated with body weight in kilogram divided by the squared height in meter. Using cut-off schemes for Asian populations [27], we categorized BMI into four groups (<18.5=1, 18.5 to 23.0=2, 23.0 to 27.5=3, >27.5=4).

Analysis

Confirmatory factor analysis of MoCA was first conducted with the whole sample to examine the measurement properties of the MoCA scale. In the second step, a mixture structural equation modeling was carried out, with MoCA as the endogenous latent variable and a categorized BMI as the observed exogenous variable. This modeling technique will identify heterogeneous subgroups that would differ the relation of BMI to MoCA. The following variables were specified as the predictors of the latent class variable, age (60 to 65=1, 65 to 69=2, 70 to 75=3, 76 to 80=4, >80=5), gender (male=0, female=1), education (no schooling=0, elementary school=1, middle school=2, high or technical school=3, associate degree or above=4), occupation (manual labor=0, mental labor=1), and disease history (no=0, yes=1).

Four mixture models (respectively of 1 through 4 classes) were estimated and compared in terms of information criteria and entropy. The best model, which was favored by lowest information criteria and highest entropy, was selected for the final report. Vuong-Lo-Mendell-Rubin Likelihood Ratio Test (LRT) and Adjusted Lo-Mendell-Rubin Likelihood Ratio Test (ALRT) indicate whether model of k number of classes significantly fit the data better than a model of with k-1 classes.

Results

Confirmatory factor analysis of MoCA

The measurement model of MoCA fit the data well, with $\chi^2_{(54)}=81.33$, $p<0.01$, CFI=0.98, TLI=0.98, RMSEA=0.03. Factor loadings of items are listed in Table 1 below. The low load factor of words recalling (5b) indicates that word recalling was not sensitive in reflecting the level of CF, which needs validation without other studies for improvement. The reliability of the scale based the variance was ω=0.86.

Mixture modeling

The information criteria, entropy, and likelihood ratio tests are listed in Table 2 below. The Bayesian Information Criteria (BIC) has been

Dimension and item No.		Item description	Factor loading
Visuospatial or executive	1a	Trace number and time words	0.70
	1b	Copy a picture of cubic	0.67
	2	Draw a clock	0.72
Naming	3	Name animal pictures	0.52
Attention	4a	Repeat numbers forward and backward	0.54
	4b	Read a long number	0.68
	4c	Subtract 100 by 7	0.67
Language	5a	Repeat sentences	0.57
	5b	Generate words	0.25
Abstraction	6	Find similarity between two things	0.64
Delayed recall	7	Delayed recall of words	0.52
Orientation	8	Tell current time and location	0.54

Table 1: Item contents of MOCA and factor loading.

	AIC	BIC	ABIC	Entropy	LRT	ALRT
One class	15352.38	15590.32	15406.26			
Two classes	8386.17	8603.49	8435.29	.81	207.62 p<0.01	204.57 p<0.01
Three classes	8336.03	8598.45	8395.34	.80	72.15 p=0.02	71.09 p=0.02
Four classes	8298.81	8606.34	8368.32	.93	71.58 p<0.01	70.53 p<0.01

Table 2: Comparison of two-class with three-class model.

	Class 1 vs. Class 2	Class 1 vs. Class 3
Gender	134.17**	132.99**
Age	-98.12**	-97.26**
Living status	44.27**	43.16
Vocation prior to retirement	-49.14**	-50.09
Education	162.66**	160.59
Monthly income	11.71**	11.49
Hobby	124.99**	124.57
History	15.89**	15.17

Table 3: Effects of covariates on class membership-multinomial logistic regression.

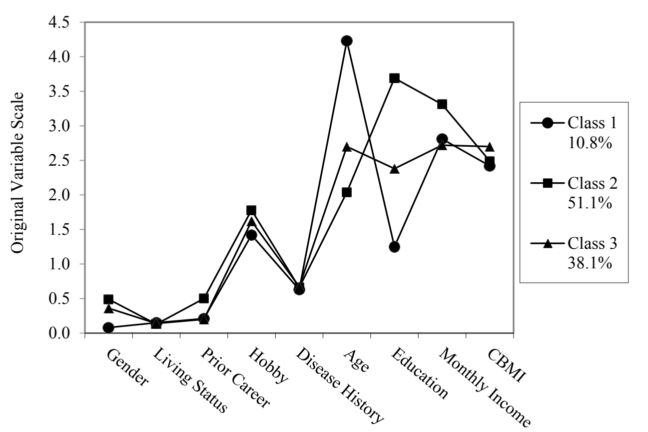

Figure 2: Profiles of three classes.

found to perform generally better than other information criteria, such as Akaike (AIC) or sample-size adjusted BIC [28]. The BIC suggested that the three-class model is slightly than the two- or four-class model. Based on the smallest Bayesian information and interpretability of the result, we chose the three-class model as the optimal for the report. The model identified 10.8% of the participants for the first class, 51.1% for the second, and 38.1% for the third. The mean of MoCA was respectively 11.55 for class 1, 16.50 for class 2, and 22.6 for class 3.

Note: AIC=Akaike Information Criterion; BIC=Bayesian Information Criterion; ABIC=Sample-size adjusted BIC.

BMI was found related to MoCA in the first class of the three-class model (β=-0.43, p=0.02), but not in the second class (β=0.02, p=0.88) or the third class (β=0.04, p=0.82). For the sake of discussion, BMI was not found related to MoCA in the one class model (β=-0.01, p=0.73).

The effects of the covariates on the latent class variable are listed in Table 3 below, as in a multinomial logistics model with Class 1 being the reference category. The large effect sizes were due to the small size of class 1, the multicollinearity of these covariates, and the default treatment of the discrete covariates as continuous. The significance of these effects suggests that these covariates contributed to the differentiation of the three classes, especially between classes 1 and 2. Specifically, classes 1 and 2 differed in all these covariates, while classes 1 and 3 differed only in gender, age and number of hobbies.

The three classes are profiled in Figure 2 below, in terms of the average levels of the covariates. Besides small differences in the covariates across the three classes, the most striking differences were in age, education, and monthly income. Class 1 had the highest age but lowest education and BMI, while class 3 had the lowest age, medium BMI, and highest the education. Class 2 was in the middle levels of age and education.

Discussion

We had hypothesized that the relation of BMI to CF was observable in extreme subsamples of BMIs, particularly in high BMI participants. Contrary to this hypothesis, only in the highest age and lowest education and BMI could a negative relation be found. No significant relation could be identified in either the whole sample or a high BMI group. Identifying a such group with specific demographic characteristics might shed some lights for intervention and preventions of mild impairment of CF.

The findings of this study seemed to suggest that a small proportion of the elderly might enrich their diet to improve their cognitive functions, instead of intentionally keeping underweight Figures. Underweight in old age could imply that the older adults are undergoing certain diseases, malfunctions of nutrient absorption, or simply malnutrition. Given that our sample was selected to have no serious diseases and the statistical modeling has controlled for disease history, this small proportion of the sample could have suffered from malnutrition, as indicated by their relatively lowest CBMI. The finding was consistent with studies that examined the relation of nutrition to cognitive functions in the older adults [15,18-20,29] and findings that overweight is unnecessarily related to impaired CF [30]. There are two possible explanations for their underweight. First, their lowest educational level might not have empowered them to obtain well-balanced nutritious diets. Another might be their intentional restraints from proper amount of diets, because of compliance to the platitude that “money cannot buy slimness in old age” in the Chinese culture. In any case, under-weight plus low education might be of serious concern.

Analytically, had we taken the variable-centered the approach to analyze the data, we could have concluded that BMI was not related to CF, as also would be consistent with some of the previous null findings in western countries and in China. With this approach to analyzing the data, the relation of BMI to MoCA might best be interpreted as the synergy of multiple variables, especially age, education, and BMI. From a heredity-environment interaction perspective, the environmental influence on the comorbidity of undesirable BMI and impaired CF should not be underestimated and discourage any feasible attempts to prevent and intervene BMI.

Conclusion

This study is limited in the following aspects. First, the data were collected cross-sectionally without any temporal precedence and the study has not probed into the genetic or biomolecular level, thus any causal relation could not be firmly concluded. Second, other aspects of life of the elderly have not been examined, so the practical meaning of this low BMI and impaired CF cannot be extended. Future, studies may apply longitudinal designs to examine to what extent the quality of life of the low BMI older adults may have been reduced concomitantly or subsequently, as it is the ultimate in the older adults. In conclusion, low BMI is related to cognitive functions in a small proportion of some older adults in China. Preventions of impaired CF may be designed accordingly.

Acknowledgment

This study was supported by the National Natural Science Foundation of China with a grant (No. 81473747) awarded to Hui Hu, College of Nursing, Hubei University of Chinese Medicine.

References

1. Smith E, Hay P, Campbell L, Trollor JN (2011) A review of the association between obesity and cognitive function across the lifespan: Implications for novel approaches to prevention and treatment. Obes Rev 12: 740-755.
2. Nilsson LG, Nilsson E (2009) Overweight and cognition. Scand J Psychol 50: 660-667.
3. Elias MF, Elias PK, Sullivan LM, Wolf PA, D'agostino RB (2003) Lower cognitive function in the presence of obesity and hypertension: The Framingham heart study. Int J Obes 27: 260-268.
4. Jeong SK, Nam HS, Son MH, Son EJ, Cho KH (2005) Interactive effect of obesity indexes on cognition. Dement Geriatr Cogn, 19: 91-96.
5. Waldstein SR, Katzel LI (2006) Interactive relations of central versus total obesity and blood pressure to cognitive function. Int J Obes 30: 201-207.
6. Kuo HK, Jones RN, Milberg WP, Tennstedt S, Talbot L, et al. (2006) Cognitive function in normal-weight, overweight, and obese older adults: An analysis of the advanced cognitive training for independent and vital elderly cohort. J Ame Geriatr Soc 54: 97-103.
7. García-Ptacek S, Faxén-Irving G, Čermáková P, Eriksdotter M, Religa D (2014) Body mass index in dementia. European J Clin Nutr 68: 1204-1209.
8. Dahl AK, Hassing LB (2013) Obesity and cognitive aging. Epidemiol rev 35: 22-32.
9. Cova I, Clerici F, Rossi A, Cucumo V, Ghirett R, et al. (2016) Weight loss predicts progression of mild cognitive impairment to Alzheimer's disease. PloS one 11: e0151710.
10. LeBlanc ES, Rizzo JH, Pedula KL, Yaffe K, Ensrud KE, et al. (2016) Weight trajectory over 20 years and likelihood of mild cognitive impairment or dementia among older women. J Ame Geriatr Soc 65: 511-519.
11. Bryant AN, Ford KL, Kim G (2014) Racial/ethnic variations in the relation between body mass index and cognitive function among older adults. Am J Geriatr Psychiatry 22: 653-660.
12. Wu YT, Lee HY, Norton S, Prina AM, Fleming J, et al. (2014) Period, birth cohort and prevalence of dementia in mainland China, Hong Kong and Taiwan: A meta-analysis. Int J Geriatr Psychiatry 29: 1212-1220.
13. Chen JM, Cui GH, Guo HD, Xu R, Jiang GX, et al. (2013) The association of weight status with cognitive impairment in the elderly population of a Shanghai suburb. Asia Pac J Clin Nutr 22: 74-82.
14. Lu Y, Lu J, Wang S, Li C, Liu L, et al. (2012) Cognitive function with glucose tolerance status and obesity in Chinese middle-aged and aged adults. Aging Mental Health 16: 911-914.
15. Isaia G, Mondino S, Germinara C, Cappa G, Aimonino-Ricauda N, et al. (2011) Malnutrition in an elderly demented population living at home. Arch Gerontology & Geriatr 53: 249-251.
16. Marioni RE, Yang J, Dykiert D, Mõttus R, Campbell A, et al. (2016) Assessing the genetic overlap between BMI and cognitive function. Mol Psychiatry 21: 1477-1482.
17. Beydoun MA, Beydoun HA, Wang Y (2008) Obesity and central obesity as risk factors for incident dementia and its subtypes: a systematic review and meta-analysis. Obes Rev 9: 204-218.
18. Fagerström C, Palmqvist R, Carlsson J, Hellström Y (2011) Malnutrition and cognitive impairment among people 60 years of age and above living in regular housing and in special housing in Sweden: A population-based cohort study. Int J Nurs Stud 48: 863-871.
19. Lee KS, Cheong HK, Kim EA, Kim KR, Oh BH, et al. (2009) Nutritional risk and cognitive impairment in the elderly. Arch Gerontology & Geriatr 48: 95-99.
20. Saragat B, Buffa R, Mereu E, Succa V, Cabras S, et al. (2012) Nutritional and psycho-functional status in elderly patients with Alzheimer's disease. J Nutr, Health & Aging 16: 231-236.
21. Wu YT, Grant WB. Prina AM, Lee HY, Brayne C (2015) Nutrition and the prevalence of dementia in mainland China, Hong Kong, and Taiwan: An ecological study. J Alzheimers Dis 44: 1099-1106.
22. Laursen BP, Hoff E (2006) Person-centered and variable-centered approaches to longitudinal data. Merrill-Palmer Q 52: 377-389.
23. Bergman LR, Trost K (2006) The person-oriented versus the variable-oriented approach: Are they complementary, opposites, or exploring different worlds? Merril-Palmer Quarter 52: 601-632.
24. Muthén B (2008) Latent variable hybrids: Overview of old and new models. In Hancock GR, Samuelsen, KM (Eds), Advances in latent variable mixture models, USA. pp. 1-24.
25. Muthén LK, Muthén BO (2012) Mplus User's Guide: Statistical analysis with latent variables. USA. pp. 688.
26. Nasreddine ZS, Philips NA, Be´dirian V, Charbonneau S, Whitehead V, et al. (2005) The Montreal cognitive assessment, MoCA: A brief screening tool for mild cognitive impairment. J Am Geriatr Soc 53: 695-699.
27. Barba C, Cavalli-Sforza T, Cutter J, Darnton-Hill I (2004) Appropriate body-mass index for Asian populations and its implications for policy and intervention strategies. The Lancet, 363: 157-163.
28. Nylund KL, Asparouhov T, Muthén BO (2007) Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. Struct Equ Modeling. 14: 535-569.
29. Soto ME, Secher M, Gillette-Guyonnet S, Van Kan GA, Andrieu S, et al. (2012) Weight loss and rapid cognitive decline in community-dwelling patients with Alzheimer's disease. J Alzheimers Dis 28: 647-654.
30. Winblad B, Amouyel P, Andrieu S, Ballard C, Brayne C, et al. (2016) Defeating Alzheimer's disease and other dementias: A priority for European science and society. Lancet Neurol 15: 455-532.

Citation: Yang C, Hu H, Wang L, Ai Y, Ren H, et al. (2017) Body Mass Index Is Related to Cognitive Function in Chinese Older Adults: So What? J Gerontol Geriatr Res 6: 437. doi:10.4172/2167-7182.1000437

OMICS International: Open Access Publication Benefits & Features

Unique features:

- Increased global visibility of articles through worldwide distribution and indexing
- Showcasing recent research output in a timely and updated manner
- Special issues on the current trends of scientific research

Special features:

- 700+ Open Access Journals
- 50,000+ editorial team
- Rapid review process
- Quality and quick editorial, review and publication processing
- Indexing at major indexing services
- Sharing Option: Social Networking Enabled
- Authors, Reviewers and Editors rewarded with online Scientific Credits
- Better discount for your subsequent articles

Submit your manuscript at: **http://www.omicsonline.org/submission//**