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Determinants of multimorbidity among elderly population in maharashtra, India: Logistic regression analysis

Reshma Santhosh, Satish V. Kakade, Durgawale PM

Abstract:

BACKGROUND: Population aging is an emerging global trend. Because of decreasing fertility rates and improved healthcare, the lifespan of elderly population increased. Consequently, proportion of elderly population is increasing at an alarming rate. This is accompanied by an increased recognition of the occurrence of multimorbidity and associated mortality risks. So, the purpose of this study was to determine the prevalence and predictors of multimorbidity among elderly population in Maharashtra with its variation among socio-demographic spectrum, functional health and health behaviors.

MATERIALS AND METHODS: Sample of elderly population aged > 60 years were selected to examine multimorbidity and its associated risk factors. Statistical methods such as Chi-square test were used to show the association between multimorbidity and other covariates. Binary logistic regression analysis was used to understand the effects of predictor variables on multimorbidity. Receiver Operating Characteristic (ROC) Curve Analysis was carried out to improve the performance of the classification model by using a modified cut-off probability value. Z scores were calculated to compare model performance in training data and test data.

RESULTS: The prevalence of multimorbidity in Maharashtra in training data and test data was found to be 32.8% and 32.9%. Residence, living arrangement, MPCE Quintile, marital status, work status, education, tobacco consumption, physical activity, Instrumental Activities of Daily Living (IADL), Activities of Daily Living (ADL) and self-rated health of elderly population were important determinants that exert a significant adverse effect on multimorbidity.

CONCLUSION: Prediction percentages indicate that appropriate actions should be undertaken to ensure good quality of life for all the elderly in Maharashtra.

Keywords:

Determinants, elderly population, multimorbidity, predictors, prevalence

Department of Community Medicine, Krishna Vishwa Vidyapeeth "Deemed To Be University", Karad, Maharashtra, India

Address for correspondence:
Dr. Satish V. Kakade, Department of Community Medicine, Krishna Vishwa Vidyapeeth "Deemed to Be University", Karad - 415 539, Maharashtra, India.
E-mail: satishvkakade1964@gmail.com

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Introduction

Multimorbidity defined as the simultaneous presence of two or more chronic diseases in an individual, usually among elderly population is an important concept in the context of aging as the proportion of elderly population is on the rise. As age increases, the likelihood of developing multiple diseases will also increases. Living with the burden of multimorbid conditions presents distinctive challenges that reflect the need for proper care and management of elder population. This paper primarily focused on the multimorbidity status of one of the most populous and diverse state Maharashtra. The share of elderly population out of 125 million people in Maharashtra accounts for 11.7%, which is higher than the national average of 10%. It is projected to increase by 15% in 2031.[1,2] Thus the present study was undertaken to determine the prevalence and predictors of multimorbidity among elderly population in Maharashtra. Analyzing morbidities among elders will provide information about

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variety of health and lifestyle risk factors, which is crucial for developing and implementing healthcare strategies.

Materials and Methods

Study design and setting

Descriptive and analytical study design was used for the analysis. The data of the first wave Longitudinal Aging Study in India (LASI) conducted in 2017–2018 across all 35 states (excluded Sikkim) and union territories (UTs) in India was used for the purpose of the present study.[3]

Study participants and sampling

For the purpose of the present study, a sample of 741 elderly population (aged 60 and above) from Maharashtra was selected. The data have been divided into two parts: training data and test data. Data of two-thirds of the total sample size of 519 elders was selected randomly for training data, and remaining one-third that is, 222, was selected for test data. The data was extracted by eliminating subjects with missing/wrongly entered/invalid data of pre-decided study parameters.

Data collection tool and technique

The parameter "Multimorbidity" was the Dependent Variable, and a score was calculated from the nine chronic conditions reported by the participants. It was then categorized into 0 = No Multimorbidity and 1 = Having Multimorbidity. Chronic Health Conditions undertaken for multimorbidity were: Chronic Heart Diseases, Diabetes mellitus, High Cholesterol, Hypertension, Stroke, Chronic Lung Diseases, Cancer, Bone or Joint diseases, Neurological or Psychiatric problems.[3] The independent variables considered for this study are, Individual Characteristics: gender, education, work status, marital status, physical activity; Household characteristics: place of residence, religion, caste, MPCE Quintile, living arrangement; Health behaviors: tobacco and alcohol consumption; Functional Health: IADL (Instrumental Activities of Daily Living) and ADL (Activities of Daily Living); Self-satisfaction: Life satisfaction and Self-Rated health. Statistical analyses such as univariate and bivariate analyses were adopted for all study variables to identify the proportion of multimorbidity conditions among elderly population. Chi-square test was presented to show the association between multimorbidity and other covariates. Unadjusted Odds Ratios, in case of a significant association are determined. Furthermore, logistic regression was performed to identify the risk factors of developing multimorbidity and to identify modifiable factors, if any. Regression models were expressed as unadjusted and adjusted odds ratios (AOR) along with its 95% confidence interval (CI) for variables significantly contributing to the prediction of multimorbidity determined to understand the risk of multimorbidity in subjects with the presence of exposure to the event in comparison to subjects with absence of exposure to the event. To assess the performance of multimorbidity we built four classification models, three in training data and one in test data. Significance level of 10% ($P \leq 0.1$) was used to select variables as predictor variables of multimorbidity during logistic regression analysis. Receiver operating characteristic (ROC) Curve Analysis was carried out to detect the cut-off probability giving an equalized classification of multimorbidity and non-multimorbidity for the logistic regression model. Finally Z test for Standard Error of Difference between two proportions was used to compare model performance in training data and test data. The data was analyzed by using the licensed copy of SPSS version 28.

Ethical consideration

LASI wave 1 2017-18 got ethical clearance from the Indian Council of Medical Research (ICMR). There is no participation risk in this study since it was based on secondary data. Request has been made from IIPS, Mumbai, through proper channels and permission has been granted by IIPS for the use of LASI data for the present study.The same has been properly acknowledged and referenced wherever required. Institutional Ethics Committee approval was received to commence the proposed study (KIMSDU/IEC/07/2021).

Results

Training data

Among 519 elders from Maharashtra, the prevalence of multimorbidity was 32.8%.

The association of multimorbidity with socio-demographic characteristics, functional health, health behaviors and life satisfaction characteristics were depicted in [Table 1]. Among 16 independent variables, Gender, Religion, Caste, Alcohol consumption, and subjective well-being have no significant association with multimorbidity ($P > 0.1$). Whereas Residence, Living Arrangement, MPCE Quintile, Marital and Work status, Education, Tobacco consumption, Physical Activity, IADL, ADL, and Self-Rated Health were found to be significantly associated with multimorbidity ($P \leq 0.1$). Unadjusted odds ratios and respective 95% CI of these significantly associated independent variables revealed that:

The odds of having multimorbidity among elders in urban areas showed 1.8 with 95% CI: 1.222 to 2.677. The chance of having multimorbidity among those who stayed alone or with only spouses/children/others was 0.6 with 95% CI: 0.4567 to 0.9573. The reduced chance of having multimorbidity among those who belong to the wealthiest MPCE Quintile was 0.6 with 95% CI 0.4342 to 0.9193 when compared to those who belong to poor/middle MPCE Quintile. In marital status, never

Table 1: Multimorbidity with socio-demographic characteristics and health behaviors among elderly

Characteristic	Categories	Multimorbidity			χ2	*P*-value
		Yes (170)	No (349)	Total (519)		
		n (%)	*n*			
Individual Characteristics						
Gender	Male	129 (31.6)	279	408	1.121	0.29
	Female	41 (36.9)	70	111		
Marital Status	Never Married/Widow/Divorced etc	41 (40.2)	61	102	3.191	0.074
	Currently Married	129 (30.9)	288	417		
Education	Secondary/Higher Education	71 (40.3)	105	176	6.957	0.008
	Primary/Middle Education	99 (28.9)	244	343		
Work Status	Working	38 (18.5)	167	205	31.1	<0.001
	Not Working	132 (42)	182	314		
Physical Activity	No	67 (37.9)	110	177	3.169	0.075
	Yes	103 (30.1)	239	342		
Household characteristics						
Religion	Hindu	143 (32.2)	301	444	0.419	0.517
	Muslim/Christian/Others	27 (36)	48	75		
Caste	SC/ST/OBC	119 (32.7)	245	364	0.002	0.963
	Open	51 (32.9)	104	155		
Residence	Rural	105 (28.8)	260	365	8.883	0.003
	Urban	65 (42.2)	89	154		
Living Arrangement	Living Alone or with Spouse/Children/Others	83 (38.1)	135	218	4.826	0.028
	Living with Spouse and Children	87 (28.9)	214	301		
MPCE Quintile	Poor/Middle	94 (28.9)	231	325	5.797	0.016
	Rich	76 (39.2)	118	194		
Health Behaviors						
Alcohol Consumption	No	141 (34.1)	272	413	1.761	0.184
	Yes	29 (27.4)	77	106		
Tobacco Consumption	No	100 (36.6)	173	273	3.926	0.048
	Yes	70 (28.5)	176	246		
Functional Health						
IADL	No	89 (28.8)	220	309	5.417	0.02
	Yes	81 (38.6)	129	210		
ADL	No	103 (28.7)	256	359	8.734	0.003
	Yes	67 (41.9)	93	160		
Self-Satisfaction						
Life Satisfaction	Low	84 (34.7)	158	242	0.791	0.673
	Medium	65 (31)	145	210		
	High	21 (31.3)	46	67		
Self-Rated Health	Good	20 (20.4)	78	98	12.37	<0.001
	Poor/Fair	53 (42.7)	71	124		

married/widowed/divorced have higher odds of having multimorbidity (OR = 1.5; 95% CI: 0.9596 to 2.347), not working (OR = 3.2; 95% CI: 2.099 to 4.839), secondary/higher education (OR = 1.7; 95% CI: 1.138 to 2.440), those who were consuming tobacco (OR = 0.6; 95% CI: 0.4750 to 0.9968, physically inactive elders (OR = 1.4; 95% CI: 0.9649 to 2.070), difficulty in IADL activities (OR = 1.5; 95% CI: 1.071 to 2.250). Similarly, disability in ADL (OR = 1.8; 95% CI 1.214 to 2.641), and poor/fair health status (OR = 3; 95% CI 1.587 to 5.340) as compared to those who have good health status.

Backward logistic regression analysis was performed to identify precise and adequate predictors of multimorbidity. The model was developed to show the prediction or classification ability with all 11 independent variables (Residence, Education, Work Status, Marital Status, MPCE Quintile, IADL, ADL, Living Arrangement, Self-Rated Health, Physical Activity, Tobacco) [Table 2]. Model classification table revealed that 29.4% of total multimorbid participants correctly predicted that they had multimorbidity while 88.5% of non-multimorbid population was correctly predicted that they had no multimorbidity. Thus, the overall correct prediction percentage of model with these variables was 69.2% with a cut-off probability 0.5; i.e., if $P \geq 0.5$ was indication of the existence of multimorbidity; otherwise ($P < 0.5$) multimorbidity was not existing.

The backward logistic regression analysis [as shown in Table 3] produced a model with four significant risk factors that affect multimorbidity. Values of categories of independent variables were showed in [Table 4]. The overall correct prediction ability of this model with cut-off probability 0.5 was 70.1% [Table 5]. The odds of multimorbidity were higher among the wealthier group (OR = 1.58; 95% CI: 1.061 to 2.359). The likelihood of multimorbidity was higher among those who are not working (OR = 2.88; 95% CI: 1.873 to 4.44), secondary/higher education (OR = 1.6; 95% CI: 1.061 to 2.439), poor/fair (OR = 2.68; 95% CI: 1.694 to 4.248) respectively.

This logistic regression model derived to determine the probability of multimorbidity using these four significant independent variables is determined as follows:

$\ln(p\ 1-p) = \propto + \beta 1\ x1 + \beta 2\ x2 + \beta 3\ x3 + \ldots \beta i\ xi + e$

where - p is the likelihood of occurrence of multimorbidity

p (y = 1); β1, β2, β3… βi refers to the beta coefficients; x1, x2, x3, …xi refers to the independent variables, and e is the error term.

P (Multimorbidity)= $1/1+e^{-}(\beta o+\beta xi)$

where

β_0 = Constant = -2.469

β_{xi} = 0.458*MPCE Quintile + 1.059*Work status + 0.475*Education + 0.987* SRH – 2.469

The values for categories of independent variables in this model should be introduced as per given in Table 4.

Table 5 shows the prediction ability of the model based on these four significant variables. The model revealed that 40.6% of multimorbid participants were correctly predicted that they had multimorbidity while 84.5% of non-multimorbid population correctly predicted that they did not have multimorbidity. Thus, overall correct prediction percentage of model with four variables was 70.1% with a cut-off probability of 0.5.

The prediction percentage of logistic regression model with four significant variables and model with all 11 study variables showed similar predictive ability. However, the correct prediction percentage of non-multimorbidity was very high as compared to correct prediction percentage of multimorbidity with a cut-off probability of 0.5.

For balancing these prediction percentages ROC curve analysis was performed [Figure 1].

ROC curve

The ROC curve analysis revealed that a cut-off probability of 0.374 could determine equalized correct prediction percentages of multimorbidity and non-multimorbidity.

Area under curve was found to be 70.3%. The optimal cut-off for determining equalized proportion of presence and absence of multimorbidity at $P = 0.374$ pointed to 69.4% sensitivity and 62.5% specificity.

When computed probabilities of multimorbidity of these 519 subjects were categorized, it revealed that

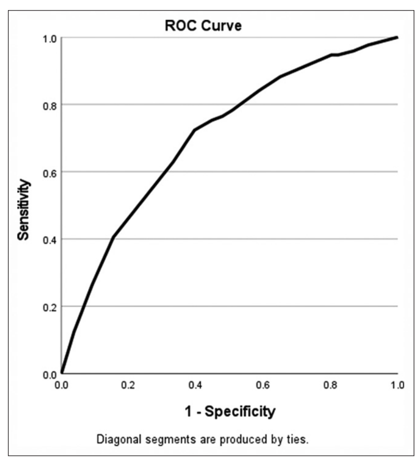

Figure 1: Receiver Operating Characteristic (ROC) Curve

Table 2: Model classification based on all 11 study variables

Observed	Predicted		
	Multimorbidity		% Correct
	Yes	No	
Multimorbidity			
Yes	50	120	29.4
No	40	309	88.5
Overall Percentage			69.2

The cut value is 0.500

Table 3: Backward logistic regression model predicting Multimorbidity using four significant variables

Independent variable	B	S.E.	Wald	df	Sig.	Adjusted OR	95% CI for Adjusted OR	
							Lower	Upper
MPCE quintile (Rich)	0.458	0.204	5.058	1	0.025	1.581	1.061	2.356
Work status (No)	1.059	0.22	23.126	1	<0.001	2.883	1.873	4.44
Education (Secondary/Higher education)	0.475	0.212	5.007	1	0.025	1.608	1.061	2.439
Self-Rated Health (Poor/Fair)	0.987	0.235	17.696	1	<0.001	2.682	1.694	4.248
Constant	-2.469	0.284	75.398	1	<0.001	0.085		

69.4% of the total multimorbid population correctly predicted that they had multimorbidity while 62.5% of non-multimorbid population correctly predicted that they had no multimorbidity [Table 6]. Thus, overall correct prediction percentage of model with these variables was 64.7% with a cut-off probability of 0.374; that is, if $P \geq 0.374$, multimorbidity exists; otherwise ($P < 0.374$) multimorbidity was not exist.

Test data

Among 222 elders from Maharashtra, the prevalence of multimorbidity was 32.9%.

The classification ability with observed and predicted presence/absence of multimorbidity was displayed in [Table 7]. Out of 222 elders, 61.6% of multimorbid participants correctly predicted that they had multimorbidity, and 58.4% of non-multimorbid participants correctly predicted that they had no multimorbidity. The overall correct prediction was 59.5%.

The model performance, whether the recommended model based on train data results in similar findings in test data, is assessed using Z-test. The null hypothesis states that H_0: There is no significant difference in the proportions of predicted multimorbidity/no multimorbidity/overall correct prediction by the logistic regression model in training and test data. Alternate hypothesis states that H1: there is a significant difference in the proportions of multimorbidity/no multimorbidity/overall correct prediction by the logistic regression model in training and test data.

Z test for standard error of difference between two proportions

The formula for Z-score used is:

Z = (p1-p2) ÷ S.E (p1-p2), where

p1 = Percentage in train data
p2 = Percentage in test data
n1 = Sample size of train data
n2 = sample size of test data

The value of standard error for Z-test can be calculated using the following formula:

$$\text{S.E (p1-p2)} = \sqrt{(\text{p1q1} \div \text{n1}) + (\text{p2q2} \div \text{n2})}$$

The value of Z-score comes out to be 1.16 for multimorbidity, 0.8 for no multimorbidity and 1.33 for overall multimorbid and no multimorbid. All the Z-score values lie in a 95 percent CI: -1.96 to + 1.96 [Table 8]. Thus, we can accept the null hypothesis based on the given evidence (sample selected). This indicates that there is no difference in the proportions of predicted multimorbidity/no multimorbidity/overall correct prediction by the logistic regression model in training data and test data.

Table 4: Values of categories of independent variables

Categorical variables	Category	Coding value
Self-Rated Health	Good	0
	Poor/Fair	1
MPCE Quintile	Poor/Middle	0
	Rich	1
Education	Primary/Middle Education	0
	Secondary/Higher Education	1
Work Status	Working	0
	Not Working	1

Table 5: Model classification based on four significant variables

Observed	Predicted		
	Multimorbidity		% Correct
	Yes	No	
Multimorbidity			
Yes	69	101	40.6
No	54	295	84.5
Overall Percentage			70.1

The cut value is 0.500

Table 6: Model classification based on four significant variables with modified cut-off

Observed	Predicted		
	Multimorbidity		% Correct
	Yes	No	
Multimorbidity			
Yes	118	52	69.4
No	131	218	62.5
Overall Percentage			64.7

The cut value is 0.374

Table 7: Model Classification between observed and predicted multimorbidity and no multimorbidity

	Model Prediction		Total
	Multimorbidity	No multimorbidity	
Multimorbidity			
Yes	45 (61.60)	28 (38.40)	73
No	62 (41.60)	87 (58.40)	149
Total	107 (48.20)	115 (51.80)	222

Discussion

This study examined the predictors of multimorbidity and studied the proportions of multimorbidity in training and test data among elderly population in Maharashtra by utilizing nationally representative data (LASI). The present study used a total sample size of 741 elders from Maharashtra, out of which 519 were used for training and 222 were used for testing the data.

Table 8: Z-statistics classification table between multimorbid, no multimorbid and overall correct prediction

Category	Correct prediction by logistic regression model out of observed with cut *P* value 0.374		Z-Value
	Training data	Test data	
Multimorbidity ($P\geq0.374$)	118/170 (69.4%)	45/73 (61.6%)	1.16
No multimorbidity ($P<0.374$)	218/349 (62.5%)	87/149 (58.4%)	0.8
Overall correct	336/519 (64.7%)	132/222 (59.5%)	1.33

Information obtained from 519 elders from training data shows 32.8% of elders aged 60 and above reported multimorbidity, which is higher than other multimorbidity study conducted in Maharashtra.[4] Similar results were obtained in a study by P Patel *et al*., 2023 and GK Mini *et al*., 2017 with NCD multimorbidity prevalence of 30.7%.[5,6] Higher prevalence of multimorbidity was observed in a study by JS Kshatri *et al*., 2020.[7] S Chauhan *et al*., 2021 study conducted all over India showed that 16% of older people reported suffering from two or more disease conditions.[8] Studies conducted in Brazilian and South African elderly exhibited a higher prevalence (81.3% and 69.4%) than the prevalence of multimorbidity in the present study. [9,10] The disparity in multimorbidity prevalence depends upon the parameters utilized for examining them.

Association of multimorbidity with 16 different variables including socio-demographic, health behaviors, functional health characteristics and self-satisfaction were employed in bivariate analysis. It was observed that Residence (urban), Living Arrangement (alone or with only spouse/children/others), MPCE Quintile (rich), Marital (never married/widow/divorced) and Work status (not working), Education (secondary/higher education), Tobacco consumption (yes), Physical Activity (no), IADL (yes), ADL (yes) and Self-Rated Health (poor/fair) were significantly associated with multimorbidity. Individuals with these characteristics were found to be more prone to experiencing multimorbidity than their respective counterparts. Similar results were obtained in study conducted by S Chauhan *et al*., 2021 and P Patel *et al*., 2023.[8,5] Elders who are staying alone may be vulnerable in terms of income which can influence health status of elderly. An extended family household may help to improve the health status of older people. Elderly people may also receive needed physical care and emotional support by staying with their family, and lack of this support will increase the chance of developing multimorbidity. In a study by Patel P *et al*., 2023 risk of multimorbidity was highest among the richest as compared to those belonged to poor/middle households who had lowest chance of developing multimorbidity.[5] The reason could be adoption of unhealthy lifestyles and also the increased chance of diagnosis of diseases. Healthcare accessibility was higher among richer individuals when compared to others. Le Duc Dung *et al*., 2016 found contrasting results that those who belong to poorer households were more likely to develop multimorbidity than wealthier individuals.[11] The possible explanation could be that healthcare facilities were easier to access for richer individuals. They could use their financial resources to afford them, along with a proper and better diet, which will result in reduction of diseases that may lead to multimorbidity. The role of marital relationship will positively influence the probability of having multimorbidity, which will affect health and well-being across the life course of elderly. In current study, those who were following sedentary lifestyle had a greater probability of the occurrence of number of diseases. Thus, poor health status will make them withdraw from workforce. Elders with no occupation had a greater chance of acquiring multimorbidity when compared to working elders. Education plays an important and primary determinant of health and well-being throughout the life course. A person's education, and even that of their parents, affects their income, access to health care, lifestyles, and social networks – all the way to old age.[1] Multimorbidity is more frequent among those who had tobacco consumption, which was 0.6 times more than non-users. Dhalwani N *et al*., 2017 also supported the finding of our study that the risk of multimorbidity was higher among smokers when compared to the reference group.[12] Physical activity is an important factor in determining one's health. Physically active elders had significantly less multimorbidity in comparison to those never engaged in any kind of physical activity. B Boro *et al*., 2022 in their study state that those who were sedentary were highly associated with having multimorbidity.[13,14] Having multiple chronic diseases may result in disability in the elderly. In our study disability was measured using IADL and ADL Limitations. P Su *et al*., 2016 examined the association between multimorbidity and ADL/IADL disability and found the number of chronic conditions had a relatively strong association with both ADL and IADL disability.[14] Multimorbidity is related to SRH, which discloses the overall well-being of the individuals. A study by GS Rana *et al*. 2022 showed elders who assessed their health status as poor had higher chance of having multimorbidity.[15]

Performance of multimorbidity was assessed by building four classification models, three in training data and one in test data. The first model was run to investigate the proportion of multimorbidity with 11 independent variables. The second model was run to examine the proportion multimorbidity with four independent covariates. The third model was executed with a modified cut-off to find the predictive ability of multimorbidity with four variables.

In test data, we used a sample size of 222 elders and estimated the prevalence of multimorbidity as 32.9%, and the overall prediction percentage from the fourth model was 59.5%. FM Albagmi *et al*., 2023 adopted a similar approach to analyzing data as training, validation, and testing with machine learning techniques.[16] Values of z-scores revealed the proportion obtained from the logistic regression model in training data and test data were the same.

Limitation and recommendation

The present study has several limitations. The data used for our study contains information on prevalence and determinants, which limits our understanding of the severity of diseases and multimorbidity. We calculated multimorbidity by computing only nine chronic diseases and if more diseases were included, the prevalence and impact of multimorbidity would be expected to be even greater. Impact of specific disease combinations or the severities of specific chronic conditions were not examined in our study. This study was based on self-reported information about chronic conditions and there is a possibility of bias in reporting as some of the respondents might not be able to recollect particular chronic conditions and there is a chance of underestimation also. Some respondents might not have had the disease due to treatment at the time of the survey, and some might not have consulted any medical professional. So, the true prevalence of multimorbidity may be under or over-reported. The study was cross-sectional in nature; therefore, there will be limitations in the understanding of causality. Future studies can make use of the findings from the present study to further explore the salient factors that impact the health of elderly in a diverse society like Maharashtra using qualitative and econometric methods.

Conclusion

In conclusion, the results of this study suggest that it is important that more factors that could influence multimorbidity should be identified; policymakers and government should focus, implement, and invest more in disease management and treatment so they can lead to healthy aging years. Geriatric issues should be addressed among the elderly, and knowledge about geriatric care should be provided to healthcare providers. Engaging older persons by establishing geriatric care centers and elderly clubs should provide that will support healthy improvement with aging.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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