

Characteristics of depressive disorders among the elderly in China

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Abstract

Background: Depressive disorders have become the second major risk factor that influences people's health worldwide, but few studies have focused on the prevalence of depressive disorders among the Chinese elderly and their characteristics of depressive disorders.

Objective: The current study is aimed at exploring the characteristics of depressive disorders in the Chinese elderly by latent profile analysis (LPA).

Methods: The subsection "CESD Depression" from the section "Cognition and Depression" of the CHARLS 2018 database was used for analysis. Latent profile models (LPM) were specified to identify subgroups.

Results: The prevalence of depressive disorders among the Chinese elderly was 34.8%. The 3-class model was selected as the optimal model, and the classes are defined as "no depressive disorder", "mild depressive disorders", and "moderate to severe depressive disorders".

Conclusion: The depressive disorders of the Chinese elderly have obvious categorical characteristics, which can provide a new idea for the precise intervention of depressive disorders in the Chinese elderly.

Keywords: Depressive disorders; The elderly; China; Latent profile analysis

Introduction

Depressive disorders have become the second major risk factor that influences people's health worldwide, which can not only harm people's physical and mental health but also bring a heavy global burden of diseases [5]. A cross-sectional study with a nationally representative sample indicated that the prevalence of depressive disorders was 6.8 % in China [7]. China has almost a fifth of the population worldwide with a large elderly population, and the problems of depressive disorders among the elderly deserve attention [5]. A systematic review suggested that the prevalence of depressive disorders in the Chinese elderly was 36.8 % [13]. The depressive disorders of the elderly can be obtained by psychological scale, but the cut-off value of scales can only reflect the overall level of depressive disorders instead of accurately identifying the characteristics of depressive disorders.

Additionally, even if two respondents respond with the same score on a scale, their answers on each item may be different. Latent profile analysis (LPA) is a statistical method that employs the latent profile model (LPM) to divide a population into multiple subgroups, and it focuses on identifying latent profiles within a population based on a certain set of continuous variables [3]. Currently, few studies have focused on the prevalence of depressive disorders among the Chinese elderly and their characteristics of depressive disorders. Following our protocol, this study is aimed at evaluating the prevalence of depressive disorders in the Chinese elderly and exploring the characteristics of depressive disorders in the Chinese elderly by LPA, thus providing a reference for further research and specific interventions on the elderly of different characteristics [6].

Methods

Data

This study used data from wave 4 of the China Health and Retirement Longitudinal Study (CHARLS 2018) database. CHARLES is a longitudinal survey aimed at being representative of the residents in mainland China aged 45 or older. The survey employed stratified

multistage cluster sampling and the final sample fell within 150 counties of 28 provinces in China [15]. Written informed consent has been obtained from all participants. Ethical approval for the CHARLS survey was granted by the Institutional Review Board at Peking University (IRB approval number: IRB00001052-11015). The

subsection “CESD Depression” from the section “Cognition and Depression” of the CHARLS 2018 database was used for analysis in the current study, which contains 19744 participants.

Measure

Center for Epidemiologic Studies Depression Scale (CES-D10) was used to measure the depressive disorders of participants in CHARLS [10,14]. The scale contained 10 items and each item was a 4-point Likert scaled (0=Never or seldom; 3=Most or all of the time). Higher total scores indicated a higher level of depressive disorders, a total score equal to or higher than 10 could indicate depressive disorders [2]. The Cronbach’s α of the scale in CHARLS 2018 was 0.810.

Statistical Analysis

Results

Prevalence of depression and model fit indices of latent profile models

The prevalence of depressive disorders among the Chinese elderly was

LPM was specified to identify characteristics of depressive disorders among the Chinese elderly. Robust maximum likelihood estimation was employed to estimate the parameters. The Lo-Mendell-Rubin(LMR) and the bootstrap likelihood ratio test (BLRT) were performed to compare the model fit improvement between models with k classes and k-1 classes, significant p values indicated a better model fit with k classes. The optimal number of classes was evaluated by the entropy, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the adjusted Bayesian Information Criterion (aBIC). The receiver operating characteristic (ROC) curve and Kappa test were employed to further assess the accuracy and precision of the models. Additionally, the interpretability of classes is also an important factor in determining the number of classes. Expectation maximization (EM) imputation was used to interpolate missing values. All the statistical analyses were completed using SAS 9.4 and Mplus 8.3.

34.8 % based on the cut-off value of CES-D10. Model fit indices for various models with different classes are displayed in table 1.

Table 1: Fitness indicators of different latent profile models

Class	AIC	BIC	aBIC	Entropy	LMR	BLRT	class membership probability
1	567528.11	567685.92	567622.36				1
2	522868.17	523112.78	523014.26	0.917	< 0.001	< 0.001	0.760/0.240
3	505411.83	505743.24	505609.77	0.923	< 0.001	< 0.001	0.186/0.692/0.122
4	498903.35	499321.55	499153.12	0.933	< 0.001	< 0.001	0.688/0.056/0.189/0.067
5	480031.08	480536.08	480332.69	0.964	< 0.001	< 0.001	0.063/0.088/0.136/0.654/0.059
6	479873.7	480465.49	480227.14	0.998	< 0.001	< 0.001	0.112/0.430/0.267/0.038/0.068/0.084
7	476629.07	477307.66	477034.36	0.889	> 0.999	> 0.999	0.070/0.077/0.423/0.253/0.068/0.056/0.053
8	472402.95	473168.34	472860.08	0.95	> 0.999	> 0.999	0.102/0.390/0.189/0.057/0.057/0.100/0.059/0.048

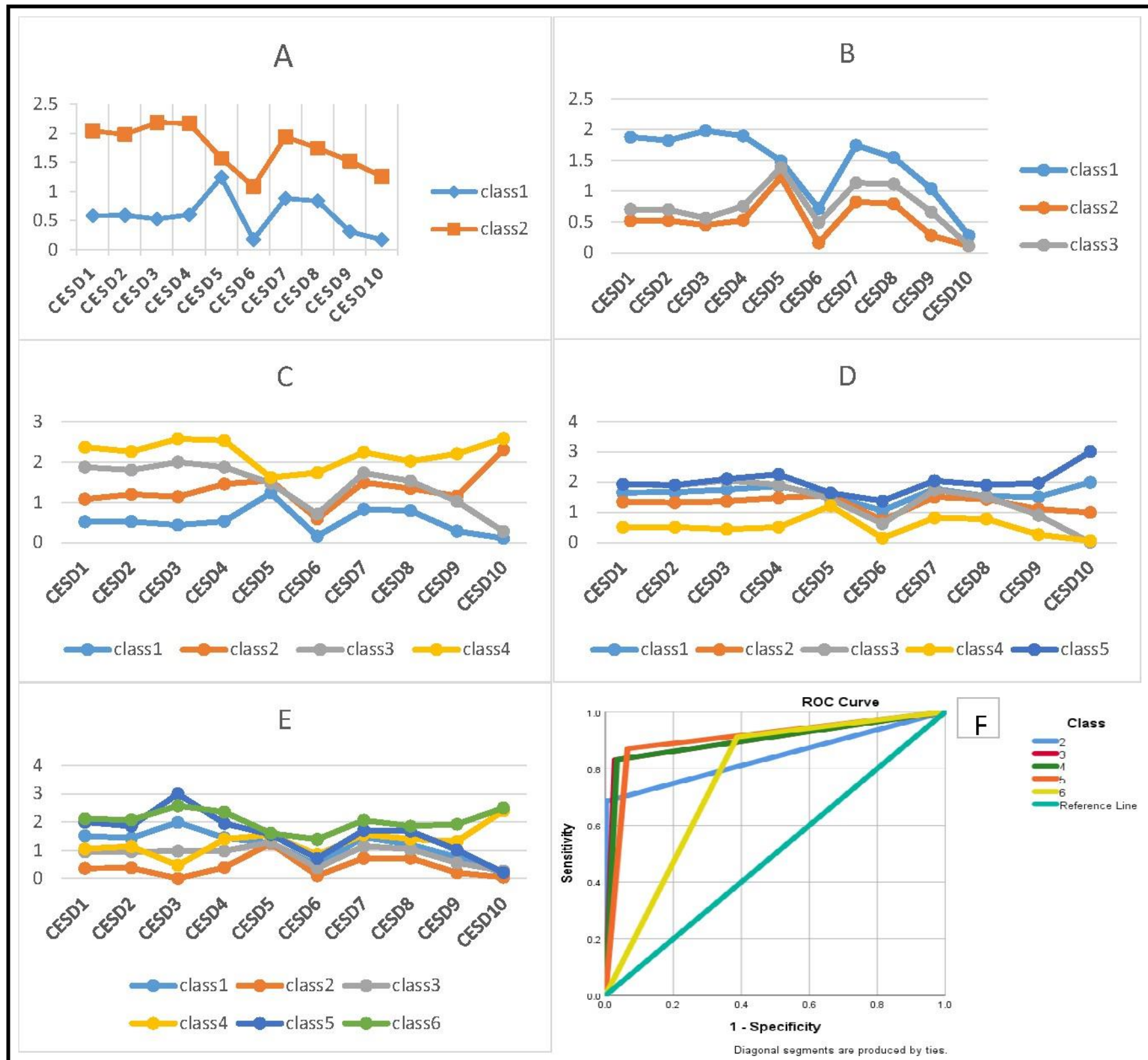
Selection of model and definition of classes

The result of **Table 1** indicated that the entropies of all classifications were above 0.8. The LMR and BLRT test was not statistically significant after the 7-class model was assigned, hence the optimal classification would be identified from the first 6 models. The AIC, BIC, and a BIC decreased with the increase in class number, and the 6-class model had the largest entropy value. The conditional means of latent classes from 2-class to 6-class are illustrated in **figure 1 (A-E)**. Assuming that the class with the lowest conditional mean of items indicated no depressive disorder, and other classes indicated certain depressive disorders in each model, to be compared with the

classification identified by the cut-off value of CES-D10. The results of the ROC curve and kappa test are shown in **Figure 1 (F)** and **Table 2**. The kappa value of the 6-class model was 0.456, suggesting it has low consistency with the scale. The 5-class model and 3-class model had the largest area under the curve (AUC) and the kappa were 0.806 and 0.826 respectively. However, the 5-class model had a low-class number probability of 0.063 and 0.088, implying that these classes may have low practical significance, therefore, considering the model fit and interpretability, the current study selected the 3-class model as the optimal model. Given the conditional mean shown in **Figure 1 (B)**, we

define class 2 as “no depressive disorder” (0.692), class 3 as “mild depressive disorders” (0.122), and class 1 as “moderate to severe

depressive disorders” (0.186).



Note: in A-E, the x axis is 10 items of CES-D, the y axis is the conditional mean of each item on each class

Figure 1: Profiles of latent classes from 2-class to 6-class and receiver operating characteristic curve

Table 2: Test of area under the curve and kappa

class	Area	SE	P	Kappa
2	0.842	0.004	< 0.001	0.737
3	0.902	0.003	< 0.001	0.826
4	0.899	0.003	< 0.001	0.818
5	0.903	0.003	< 0.001	0.806
6	0.762	0.003	< 0.001	0.456

Discussion

The current study suggested that 69.2 % of the Chinese elderly had no depressive disorder, 12.2 % had mild depressive disorders, and 18.6 % had moderate to severe depressive disorders. The conditional mean of item 6 (I felt fearful) and item 10 (I could not get “going”) were all similar and low in the 3 classes, indicating that the Chinese elderly seldom had a feeling of fear, and they thought they can continue their

life anyway. On the contrary, the 3 classes had a similar and high conditional mean of item 5 (I did not feel hopeful about the future), implying that despite the intention to continue their life, the Chinese elderly could be worried and hopeless about their future yet. Hopelessness has been regarded as a risk factor for major depression [4]. Hence, the relative department could consider improving the

hopefulness of the elderly, such as alleviating the discrimination towards them and enhancing their social support, to further prevent the occurrence or development of depressive disorders among the Chinese elderly [9].

The result of this study indicated that in the class “moderate to severe depressive disorders”, item 1 (I was bothered by things that don’t usually bother me), item 2 (I had trouble keeping my mind on what I was doing), item 3 (I felt depressed), item 4 (I felt everything I did was an effort), and item 7 (My sleep was restless) had higher conditional mean compared with other two classes, suggesting that the Chinese elderly with moderate to severe depressive symptoms usually experience anxiety, mindlessness, sadness, fatigue, and sleep disorders,

which are all characteristic symptoms of depressive disorders [1,8,12]. The relative department could consider implementing psychological interventions such as mindfulness practice to alleviate these symptoms and reduce depressive disorders among the Chinese elderly [11].

Conclusion

This study identified three latent classes to characterize the depressive symptoms of the Chinese elderly, which could provide a reference for accurate intervention. researchers could continue to explore the characteristics of depressive disorders in the Chinese elderly and their influencing factors based on the findings of this study.

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