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Cognitive ageing trajectories and mortality of Chinese oldest-old

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ABSTRACT

Objective: This study aims to identify distinctive cognitive trajectories jointly with mortality probabilities and to explore factors related to the particular trajectories of cognitive ageing in China.
Method: 6842 individuals aged 80 years and above from 7 waves of the Chinese Longitudinal Healthy Longevity Survey were assessed with the Mini-Mental State Examination for up to 16 years. A group-based trajectory model was used to jointly estimate cognitive ageing and mortality trajectories; and to explore the factors related to membership of the trajectory groups.
Results: A four-group model best fit the data. For all groups, the cognitive function declined with age according to different rates. Group 4, 3, 2, and 1 showed slow (prevalence 52.8%), moderate (31.1%), progressive (12.6%) and rapid (3.5%) cognitive decline, respectively. Mortality probability trajectories followed a hierarchy in consistence with cognitive trajectories approximately. Females, illiteracy, and those born in rural areas were less likely to belong to the most favorable trajectory group.
Conclusions: The heterogeneity of cognitive ageing was identified among Chinese oldest-old. Childhood socioeconomic status, especially education, was associated with the rate of cognitive decline.

1. Introduction

The increase in life expectancy led to rapid population ageing in the world and an unprecedented "dementia epidemic" (Larson, Yaffe, & Langa, 2013). According to World Health Organization, about 47.5 million people are suffered from dementia around the world, 90%–98% of whom are older than 65 years (Prince et al., 2015). The number of people living with dementia is estimated to almost double every two decades to 74.7 million in 2030 and 131.5 million in 2050 (Prince et al., 2015). More than half of the increase will occur in low and middle income countries. As the biggest developing country, China with the most ageing population also has the largest population with dementia (Xu, Wang, Wimo, Fratiglioni, & Qiu, 2017). In 2015, there are 9.8 million Chinese people living with dementia (Prince et al., 2015). Older people with dementia will decrease quality of life (Zhou, Fu, Hong, Wang, & Fang, 2017) and increase risk of disability (Yaffe et al., 2010) and mortality (Miller & Weissert, 2000; Yaffe et al., 2010), causing huge burdens on the patients themselves, their families, the healthcare system and the whole society. Meanwhile, the economic burden of disease care is huge, the total estimated worldwide cost of dementia is $ 818 billion in 2015 (Prince et al., 2015). In China, taking care a person with dementia will cost ¥ 1159 per month at average (Wu, Gao, Chen, & Dong, 2016).

Cognitive ageing is a dynamic process varying across individuals, including the rate and extent of cognitive decline (Mungas et al., 2010; Wilson et al., 2002). There may be some "phenotypes" ranging from optimal cognitive function to dementia during the process of cognitive ageing (Driscoll et al., 2006; Han, Gill, Jones, & Allore, 2016; Mungas et al., 2010), resulting from different developmental mechanisms determined by gene (de Magalhaes & Sandberg, 2005) and cumulative environmental exposure (Mitnitski & Rockwood, 2008). Hence identifying heterogeneity of the cognitive function declining is vital for finding out characteristics associated with different patterns of cognitive ageing in order to conduct targeted interventional strategies and reduce the burden of cognitive impairment (Han et al., 2016; Mungas et al., 2010; Yaffe et al., 2010).

Several studies from developed countries, such as Sweden, UK and USA, have elucidated cognitive ageing trajectories to show their

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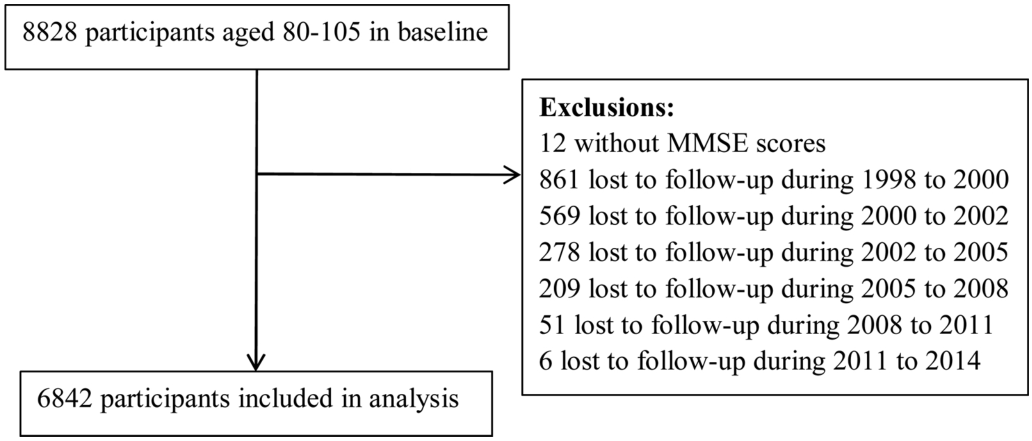

Fig. 1. The flowchart of sample selection.

heterogeneity (Han et al., 2016; Hayden et al., 2011; Small & Backman, 2007; Terrera, Brayne, & Matthews, 2010). Similarly, all researches showed that a majority of elders experienced no or only slow cognitive decline and a minority exhibited rapid cognitive decline. They demonstrated that possible factors such as sex, education and race were associated with the rate of cognitive decline. However, these studies aimed at elders with a mean age at around 80 years old. We understand that cognitive decline (depending on the specific cognitive domain) can start and progress during the period from middle to older adulthood. While the "dementia epidemic" is largely caused by the prevalence of dementia in people aged 80 or older (Larson et al., 2013). Thus, cognitive ageing trajectories of those oldest-olds are worthy of observation. Given evidence from both longitudinal (Terrera et al., 2010) and cross-sectional (Zhang, Gu, & Hayward, 2008) studies that education is associated with the cognitive function, Chinese elders with lower literacy rates than those from developed countries may have different patterns of cognitive ageing which needed to be identified. However, to our knowledge there is few researches, which focused on exploring cognitive ageing developmental heterogeneity of oldest-olds and their relative predictors using longitudinal data in developing countries (Chen & Chang, 2016).

Therefore, based on seven-wave data from Chinese Longitudinal Healthy Longevity Survey (CLHLS), this study aims to identify the distinctive trajectories of cognitive ageing jointly with mortality probability using the group-based trajectory model among oldest-olds from China, the biggest developing country. Meanwhile, to explore associations between cognitive trajectory group membership and several individual demographic characteristics and socioeconomic status (SES) often related to cognitive function decline.

2. Methods

2.1. Data sources

The data used in this study was from CLHLS, which aimed to know the oldest-old aged over 80 years in China and to explore what factors (like social, economic, biological and environmental risk factors) could influence healthy ageing. The baseline survey was conducted in 1998, until now six follow-up surveys with replacements for deceased elders were conducted in 2000, 2002, 2005, 2008/09, 2011/12, and 2014 in a randomly selected half of the counties and cities in 22 Chinese provinces. The whole survey areas covered 1.1 billion people, 85% of the total population in China. The CLHLS attempted to interview all centenarians (aged 100+) who voluntarily agreed to participate in the study in the randomly selected counties and cities of the 22 provinces. For each centenarian, one nearby octogenarian (aged 80–89) and one nearby nonagenarian (aged 90–99) were interviewed (Yi & Vaupel, 2002). Appropriate weights were calculated to match the age-sex-residence distribution of the population aged over 80 years old in 1998 (Yi, Vaupel, Xiao, Zhang, & Liu, 2001). A detailed description of the survey design had been described previously (Yi & Vaupel, 2002). The 1998 survey finally collected 9093 valid questionnaires, the age and sex distributions of the samples were shown in Supplementary Table 1. The participation rate was 88% if those who were too sick to interview or who had migrated before the interview were considered as non-participants. If these people were excluded, the participation rate was 98% (Yi et al., 2001). Previous general data quality assessment of CLHLS has shown that the quality of CLHLS data was high in the aspect of such as data completeness, reliability and validity (Gu, 2008).

The interview along with a basic health examination took place at each interviewee's home (or institution) by an enumerator and a nurse or a medical school student. Questionnaires of CLHLS contained basic information, life evaluation and personality, cognitive function, life style, ability of daily living and personal background (Yi & Vaupel, 2002).

The Research Ethics Committees of Duke University and Peking University granted approval for the Protection of Human Subjects for the CLHLS. The survey participants provided written informed consent before the survey.

2.2. Study samples

Since the CLHLS included samples at the advanced ages, it was well suited for the exploration of late-life cognitive decline trajectories in conjunction with mortality after 80 years old. Because self-reported age after 105 years is not reliable (Zeng, Vaupel, Xiao, Zhang, & Liu, 2002), the current study limited the samples to those aged 80–105 at baseline. Thus, we excluded 64 elders younger than 80 years and 201 centenarians aged 106 or above from 9093 participants. 8828 oldest-olds aged 80 to 105 were involved in analysis. Then, 12 cases were excluded as they missed all answers to Mini-Mental State Examination (MMSE) at one or more waves. We further excluded 1974 participants who were lost to follow-up in the 6 following waves of the survey due to non-death reasons. Thus, the final sample size was 6842 participants including the survivors and the decedents in each wave, of which 2726 were males and 4116 are females (Fig. 1). Details of participants in each waves were shown in Supplementary Table 2.

2.3. Variables and measurement

2.3.1. Assessment of cognitive function

In order to adapt Chinese culture, cognitive function in this study was measured by the Chinese version of MMSE, which was modified based on the international standard MMSE questionnaire (Folstein,

Folstein, & McHugh, 1975) and tested by pilot survey interviews (Yi & Vaupel, 2002). MMSE is a common tool widely used in assessing global cognitive function and screening cognitive impairment in both research and clinical settings (Han et al., 2016). In the Chinese version of MMSE, there were items including orientation, reaction time, calculation, recall, and language. Participants will get one score for each correct answer (Hu et al., 2018). Thus, MMSE had a total score range from 0 to 30, with lower scores indicating worse cognitive function.

2.3.2. Predictors of cognitive ageing

Predictors were chosen based on four principles. The first was available in CLHLS. The second was parsimonious, because of the purpose to seek basic elements of the already complicated joint modeling of cognitive ageing and death probability trajectories. The third was choosing predictors that previous studies demonstrated their associations with cognitive impairment in China (Hu et al., 2018), like birthplace and education. The fourth principle was that we avoided choosing variables that may be influenced by cognitive ageing trajectories themselves. For example, we didn't involve indicators of health behaviors, social engagement or co-residence, which may be both the cause and consequence of changes in cognitive function (Zimmer, 2008; Zimmer, Martin, Nagin, & Jones, 2012).

Demographic characteristics and SES at baseline were used as predictors. Demographic characteristics included sex, birthplace, marital status and residence. Residence and birthplace was dichotomized as urban or rural. Marital status was classified as married, divorced/separated, widowed and never married. SES included job and education. The CLHLS collected respondents' occupation through a question 'What was your main occupation before age 60?' There were nine possible answers: professional and technical personnel; governmental, institutional or managerial personnel; agriculture, forest, animal husbandry; fishery worker; industrial worker; commercial or service worker; military personnel; housework and other. We combined the first and second answers as professional/ administrative group. We categorized agriculture and housework as separate groups, because it was the most common occupation in that time. Other answers were combined together as the other group. Education was defined as illiterate who haven't received any education and literate.

2.4. Statistical methods

The basic characteristics of study samples at baseline were summarized using means ± standard deviation or frequency (percentages). In order to compare the differences in variables between sexes, we made Chi square tests for categorical variables and t-tests for continuous variables.

In our analysis, we applied group-based trajectory model (GBTM) to identify the developmental trajectories of cognitive function based on MMSE scores with age (Jones, Nagin, & Roeder, 2001). We also used an enhanced version of GBTM to jointly estimate the trajectory of cognitive ageing and the probability of nonrandom dropping out due to death by age (Haviland, Jones, & Nagin, 2011). The GBTM was based on finite mixture modeling and used maximum likelihood to identify groups of individuals following similar developmental trajectories (Nagin & Odgers, 2010; Nagin, 1999). The trajectories were usually modeled as a polynomial function of age. The parameters and orders of the polynomial were group-specific, thus it allowed different patterns of trajectories to vary with age.

We first conducted a basic model without covariates in order to determine the optimal number of groups and parameters of the polynomial functions of age that identify the trajectory for each group. We used a two-stage model selection process described by Nagin (2005) to search for the best-fit model. The focus of the first stage was to determine the number of groups to include in the model. Then in the second stage, the focus turned to determine the optimal order of the polynomial specifying the shape of each trajectory. In the model selection process, we made the choice relying on a combination of the Bayesian Information Criterion (BIC) and diagnostic tests based on posterior probabilities; meanwhile we balanced the objective of capturing the distinctive developmental patterns of the data and model parsimony. A posterior probability was a postestimation calculation what indicated the estimated possibility that an individual belonged to each group (Zimmer, Martin, Jones, & Nagin, 2014). If in a model the proportions of the sample assigned to groups based on highest posterior probabilities were about equal to the proportions generated by the maximum likelihood assignments, it indicated a good fit of the model. In order to seek the optimal model, we screened numerous potential solutions to specify each group trajectory, including varying numbers of groups with varying orders of polynomials of age.

In our model, cognitive function were assessed by MMSE scores. Our analysis included those survivors who were interviewed at all seven waves and those decedents died at the following waves. Those who dropped out the surveys for reasons other than mortality were not included in the analysis. MMSE scores were modeled as a polynomial function of age, with specific order of age polynomial depending on the group. Mortality was modeled as a function of age at survey wave prior to death. To facilitate model convergence, age was calculated as a scaled variable that is one-tenth of its original value (Zimmer et al., 2012). We used the censored normal distribution in modeling and set the minimum to 0 and maximum to 30 for MMSE scores.

Then, based on the best-fit basic model we chose, we added all predictors we mentioned before to refit a final model. In this model extension, we could simultaneously estimate trajectory group shapes; and the relationship between predictors and the estimated posterior probability of trajectory group membership by a multinomial logistic regression at the same time. That is, the final model allowed for the simultaneous estimation of the parameters determining trajectory shapes and the multinomial logit parameters that specify the associations of the predictors to the probabilities of trajectory group membership (Roeder et al., 1999; Zimmer et al., 2012).

2.5. Sensitivity analyses

We conducted three sensitivity analyses to assess the robustness of our trajectory model. First, given significantly different baseline characteristics between sexes shown in Table 1, we conducted the first sensitivity analysis to estimate trajectory models separately for males and females. For our second sensitivity analysis, we calculated the answer "not able to answer" and missing value in MMSE as a score of 0.5 as opposed to a score of 0 in our main analysis to avoid underestimating cognitive function of participants. In our main analysis, nondecedents lost to follow-up were excluded because we couldn't jointly model both mortality and other survey attrition (Zimmer et al., 2012). The third sensitivity analysis included both mortality dropouts and nonmortality dropouts to assess the effects of those lost to follow up.

3. Results

3.1. Participants and basic information

Table 1 showed that the 6842 participants had an average age of 93 (± 9.47) years at baseline. Females were older than males. About a third of participants lived in urban areas for both males and females. Nearly 95% of females were widowed, the corresponding proportion of males was 66.2%. More males had high-income jobs like professors and administrators (10.8% for males vs 1.7% for females). It's worth noting that differences were significant between sexes in having education. 60% of males had received schooling, however only 10% of females had gone to school. Less than 15% of males and females were born in urban areas. Males had significant higher MMSE scores at average (23.49 for males vs 18.50 for females).

Table 1
Basic characteristics of the samples at baseline.

N	All 6842	Male 2726	Female 4116	p-value
Age	93.42 ± 7.32	91.22 ± 6.89	94.88 ± 7.24	< 0.001
Residence				0.016
Urban	2259 (33.0)	946 (34.7)	1313 (31.9)	
Rural	4583 (67.0)	1780 (65.3)	2803 (68.1)	
Marital status				< 0.001
Married	1061 (15.7)	871 (32.7)	190 (4.6)	
Divorced/ separated	67 (1.0)	31 (1.2)	36 (0.9)	
Widowed	5633 (83.3)	1764 (66.2)	3869 (94.5)	
Never married	0	0	0	
Missing data[a]	81 (1.2)	60 (2.2)	21 (0.5)	
Job				< 0.001
Professional/ administrative	363 (5.3)	295 (10.8)	68 (1.7)	
Housework	1287 (18.8)	26 (1.0)	1261 (30.7)	
Agriculture	4031 (58.9)	1652 (60.6)	2379 (57.8)	
Others[b]	1159 (16.9)	753 (27.6)	406 (9.9)	
Missing data[a]	2 (< 0.1)	–	2 (< 0.1)	
Birthplace				0.270
Urban	876 (12.8)	364 (13.4)	512 (12.4)	
Rural	5965 (87.2)	2362 (86.6)	3603 (87.6)	
Missing data[a]	1 (< 0.1)	–	1 (< 0.1)	
Education				< 0.001
Illiterate	4745 (69.7)	1080 (39.7)	3665 (89.6)	
Literate	2064 (30.3)	1640 (60.3)	424 (10.4)	
Missing data[a]	33 (0.5)	6 (0.2)	27 (0.7)	
MMSE score	20.49 ± 9.16	23.49 ± 7.76	18.50 ± 9.47	< 0.001

Note. MMSE = Mini-Mental State Examination. Data is presented as mean ± standard deviation or n (%).
[a] Missing data is excluded from other percentage calculation.
[b] This category included fishery worker, industrial worker, commercial or service worker, military personnel and other jobs not mentioned.

3.2. Cognitive function trajectory

Among the selection of trajectory models of one to six groups with order parameters varying through linear, quadratic and cubic terms, four-group model best fit the data based on BIC tests (−53165.04 for the number of observations; −53157.06 for the number of participants) and the diagnostic test based on posterior probabilities. Table 2 showed that the proportions of the sample assigned to the groups of the basis of highest posterior probabilities for Group 1, 2, 3 and 4 were 2.6%, 12.3%, 18.5%, and 66.6%, respectively. They were almost equal to the proportions generated by the maximum likelihood, which were 3.5%, 12.6%, 31.1% and 52.8% for Group 1, 2, 3 and 4, respectively, indicating the model fitted good. Trajectory of cognitive function for Group1 was described with an intercept and a single linear age parameter. Other three groups were described with an intercept and linear and quadratic age parameters. For mortality, each group was modeled with an intercept and linear scaled age at previous wave. All

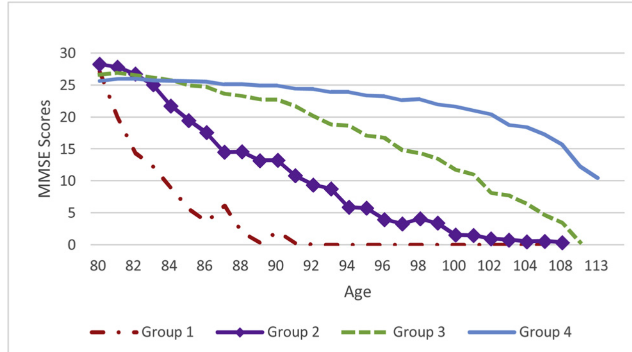

Fig. 2. Predicted trajectories of MMSE scores by group.

coefficients were significantly positive, indicating that mortality increased with age (see Supplementary Table 3 for details).

Regardless of group, the trajectories of cognitive function were decreasing with age roughly. The trajectories of cognitive ageing showed heterogeneity, plotting a descending hierarchy from Group 4 to Group 1 in Fig. 2. About 3.5% participants showed rapid decline (Group 1), whereas the others following a path of progressive (Group 2, 12.6%), moderate (Group 3, 31.1%) and slow (Group 4, 52.8%) decline, respectively. The results of three sensitivity analyses were not substantially different from the results of our main analysis. (Details were shown in Supplementary Figs. 1–4 and Supplementary Table 4).

In Fig. 3, predicted probabilities of mortality trajectories for four groups followed a hierarchy in consistence with MMSE scores trajectories approximately. Participants in rapid decline group (Group 1) could survive to the following survey wave were extremely rare above age 96. The mortality probabilities of progressive decline group (Group 2) were in the middle position. The trajectories of moderate decline and slow decline group (Group 3 and 4) nearly coincided.

3.3. Factors related to the trajectories

Table 3 presented the multinomial logit model that related individual-level predictors to posterior probabilities of trajectory group membership. This model was simultaneously estimated with trajectories themselves. Slow decline group (Group 4) with highest MMSE scores was the reference group. Thus, we made a comparison between the probabilities of membership in groups which had less favorable trajectories (Group 1, 2, and 3) and the probability of membership in the group which had the most favorable trajectory (Group 4).

In Table 3, we found that sex, birthplace and education were significantly associated with the group membership in all three groups. Females were more likely than males to be in the less favorable trajectories in comparison with Group 4. Participants who were born in rural areas had significantly higher odds of being in Group 1, 2 and 3 relative to Group 4 than those born in urban areas. Illiterate

Table 2
Maximum likelihood estimates for MMSE scores and mortality probability trajectories by sex (standard errors in parentheses).

	Group 1	Group 2	Group 3	Group 4
MMSE scores				
Intercept	24.22 (1.38)*	34.64 (1.04)*	28.38 (0.75)*	26.37 (0.44)*
Linear scaled age	−32.70 (3.14)*	−24.02 (2.29)*	−1.08 (1.50)	1.25 (0.69)
Quadratic scaled age	–	2.60 (0.95)*	−3.59 (0.49)*	−1.78 (0.24)*
Mortality probability				
Intercept	−2.15 (0.41)*	−2.54 (0.21)*	−1.39 (0.13)*	−0.81 (0.08)*
Age at previous wave scaled	4.17 (0.73)*	2.15 (0.18)*	0.97 (0.08)*	0.59 (0.04)*
Group size (%)	3.5	12.6	31.1	52.8
BIC	−53165.04 (N = 13,687); −53157.06 (N = 6842)			

Note. MMSE = Mini-Mental State Examination. BIC = Bayesian Information Criterion.
* $p < 0.01$.

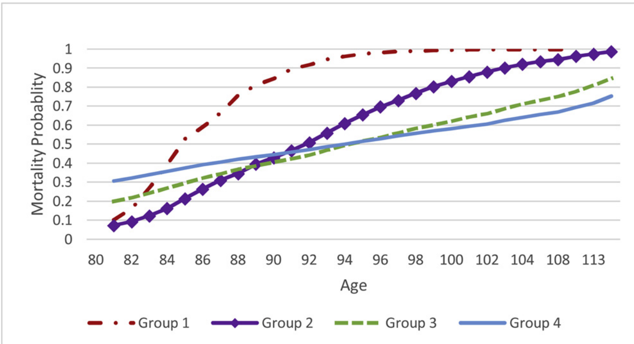

Fig. 3. Predicted trajectories of mortality probability by group.

participants were more likely to be in the less favorable groups. Married participants as opposed to those widowed had higher probabilities to be in Group 1 compared with Group 4. Living in rural areas was positively associated with the probabilities of being in Group 3 compared with Group 4.

4. Discussion

Among this oldest-old cohort followed more than 16 years in China, we applied a group-based trajectory model to jointly estimate the trajectory of cognitive ageing and the probability of nonrandom dropping out due to mortality. We identified four distinct cognitive trajectories with different rates of cognitive decline. Participants who were female, illiterate, and born in rural areas had greater risks to be clustered into groups with worse cognitive function (like Group 1, 2, and 3). Our findings focused on oldest-olds and demonstrated the existence of multiple developmental cognitive ageing trajectories in developing country, which supported that cognitive ageing is a heterogeneous process in diverse individuals, rather than a homogeneous average one (Han et al., 2016; Hayden et al., 2011).

Be consistent with previous studies, we documented hierarchical and diverging trajectories of cognitive ageing. The moderate, progressive, and rapid cognitive decline groups found in American elders were similar to our Group 3, 2, and 1 respectively in terms of group shape (Han et al., 2016). A starting high and declining group with 51.8% of participants found in Taiwan elders was similar to our Group 4 in terms of group shape and prevalence (Chen & Chang, 2016). However we didn't find a group without cognitive function decline, the reason may be that the participants were younger in those studies, 78.4 and 70.95 years old at average in American study and Taiwan study, respectively. These similar findings across studies highlight the importance to identify "phenotypes" of cognitive ageing (Han et al., 2016).

In our findings, trajectories of mortality probabilities by group followed the similar hierarchy of cognitive ageing trajectories, indicating the association between cognitive function and mortality. That is, participants in the best cognitive function group had the lowest mortality probability, and participants in the worst cognitive function group had the highest mortality probability at most time. Although previous studies had demonstrated that cognitive impairment was associated with an increased risk for mortality (Nguyen, Black, Ray, Espino, & Markides, 2003; Wu et al., 2014), they only paid attention to a static association. Our studies extended these studies by using a developmental methodology of group-based trajectory model to jointly estimate the dynamic nature of the association between cognitive function and mortality. We believe that this feature of analysis is essential, given the likely close relation of the time path of cognitive ageing and the probability of dying.

We found that females had lower MMSE scores and were associated with less likely membership in the most favorable trajectory (Group 4) compared with males. This finding was consistent with the Taiwan study, more females were in the less favorable cognitive function group (Chen & Chang, 2016). However, studies in developed countries didn't find this difference between sexes (Han et al., 2016; Hayden et al., 2011). Due to the preference for sons in traditional Chinese society, females may face tougher early life than males with worse nutrition (Zhang et al., 2008) and less chance to obtain education (Yi, Gu, & Land, 2007). The extremely large gap of education level between sexes could explain majority of the differences in MMSE scores and cognitive ageing (Lee, Shih, Feeney, & Langa, 2014).

We also found that there was a close association between birthplace and trajectory membership rather than current residence. The protective effect of early life urban residence was consistent with previous studies (Hall, Gao, Unverzagt, & Hendrie, 2000; Zhang et al., 2008) that childhood rural residence was linked to an increased risk of cognitive

Table 3
Odds ratios (OR) of characteristics in baseline to MMSE group membership by multinomial logistic regression.

	Trajectories (ref = Group 4)					
	Group 1		Group 2		Group 3	
Predictor in baseline	OR	95% CI	OR	95% CI	OR	95% CI
Sex (ref = male)						
Female	2.32**	1.59-3.40	3.33**	2.68-4.13	8.51**	6.99-10.35
Residence (ref = urban)						
Rural	1.01	0.71-1.44	0.96	0.80-1.16	1.17*	1.00-1.37
Marital status (ref = widowed)						
Married	1.61*	1.09-2.38	0.74*	0.57-0.97	0.69**	0.54-0.88
Divorced/separated	1.00	0.24-4.20	0.62	0.26-1.50	0.75	0.39-1.45
Job (ref = agriculture)						
Professional/administrative group	0.84	0.37-1.92	1.16	0.76-1.77	0.67	0.40-1.15
Housework	0.89	0.57-1.38	1.43**	1.16-1.75	1.05	0.89-1.24
Others[a]	1.26	0.82-1.94	0.79	0.61-1.04	0.77*	0.61-0.97
Birthplace (ref = urban)						
Rural	2.20**	1.29-3.76	2.22**	1.69-2.93	3.73**	2.89-4.83
Education (ref = illiterate)						
Literate	0.59**	0.40-0.87	0.66**	0.53-0.82	0.29**	0.23-0.36

Note. CI = confidence interval. MMSE = Mini-Mental State Examination.
[a] This category included fishery worker, industrial worker, commercial or service worker, military personnel and other jobs not mentioned.
** $p < 0.01$.
* $p < 0.05$.

impairment. In the early twentieth century in China, there were quite large gaps between urban and rural in the socioeconomic environment. Because of lack of public health and sanitary, the condition in rural was much worse than urban areas (Zhang & Kanbur, 2005). The higher standard of living in urban areas compared with rural areas may be the protective reasons (Zhang et al., 2008). In some degree, elders who were born in rural areas had fewer opportunities to receive schooling. We found participants with education were strongly associated with the likely memberships in the most favorable trajectory (Group 4), which was consistent with previous studies (Hall et al., 2000; Hu et al., 2018; Lievre, Alley, & Crimmins, 2008). Hall pointed that childhood rural residence, combined with less education, was associated with an increased risk of Alzheimer's disease in African Americans (Hall et al., 2000). Higher education, especially in the early twentieth century of China, indicated higher socioeconomic status with better healthcare and nutrition to help brain development (Lievre et al., 2008). In addition, individuals with less education may reach old age with less cognitive reserves (Stern, 2002). Being female, born in rural area, and receiving none education were markers for other accompanying deleterious socioeconomic or environmental influences in childhood, supporting the finding that low early life SES would increase the risk of cognitive function declining in old age (Zhang et al., 2008).

There are some limitations should be mentioned. Firstly, we used MMSE to evaluate cognitive function rather than comprehensive clinical evaluations. The clinical evaluations are more accurate, however due to budget limitations, CLHLS didn't conduct clinical tests. MMSE is the most commonly used assessment for cognitive impairment (Folstein et al., 1975). Secondly, due to CLHLS design was focused on the oldest-old, these samples survived the tough childhood and adulthood may be a selected group. They preferred to be robust in health. However, as we identified heterogeneity of cognitive ageing, which may mean these samples we employed could achieve our objectives. Thirdly, we didn't involve interactions between predictors and time-varying covariates such as health behaviors and social engagement, further studies may add these aspects to explore more influencing factors of cognitive ageing.

In conclusion, we identified four distinct cognitive trajectories jointly with mortality probabilities for Chinese oldest-old and demonstrated their relationships with predictors. These findings provide empirical evidence from a developing country for the heterogeneity of cognitive ageing and the association between early life conditions and rate of cognitive decline at advanced age. Preventive strategies should be designed accordingly to delay the cognitive function decline, especially among females and elders without enough education.

Conflict of interest

The authors declare that there is no conflict of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.archger.2019.01.018.

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