Journal of Affective Disorders 330 (2023) 24–32

Contents lists available at ScienceDirect

Journal of Affective Disorders

journal homepage: www.elsevier.com/locate/jad

Association between multimorbidity trajectories, healthcare utilization, and health expenditures among middle-aged and older adults: China Health and Retirement Longitudinal Study

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A R T I C L E I N F O

Keywords:
Multimorbidity
Healthcare utilization
Health expenditures
Group-based multi-trajectory modeling
Longitudinal analysis

A B S T R A C T

Background: To identify the latent groups of multimorbidity trajectories among middle-aged and older adults and examine their associations with healthcare utilization and health expenditures.
Methods: We included adults aged ≥45 years who participated in the China Health and Retirement Longitudinal Study from 2011 to 2015 and were without multimorbidities (<2 chronic conditions) at baseline. Multimorbidity trajectories underlying 13 chronic conditions were identified using group-based multi-trajectory modeling based on the latent dimensions. Healthcare utilization included outpatient care, inpatient care, and unmet healthcare needs. Health expenditures included healthcare costs and catastrophic health expenditures (CHE). Random-effects logistic regression, random-effects negative binomial regression, and generalized linear regression models were used to examine the association between multimorbidity trajectories, healthcare utilization, and health expenditures.
Results: Of the 5548 participants, 2407 developed multimorbidities during follow-up. Three trajectory groups were identified among those with new-onset multimorbidity according to the increasing dimensions of chronic diseases: "digestive-arthritic" (N = 1377, 57.21 %), "cardiometabolic/brain" (N = 834, 34.65 %), and "respiratory/digestive-arthritic" (N = 196, 8.14 %). All trajectory groups had a significantly increased risk of outpatient care, inpatient care, unmet healthcare needs, and higher healthcare costs than those without multimorbidities. Notably, participants in the "digestive-arthritic" trajectory group had a significantly increased risk of incurring CHE (OR = 1.70, 95%CI: 1.03–2.81).
Limitations: Chronic conditions were assessed using self-reported measures.
Conclusions: The growing burden of multimorbidity, especially multimorbidities of digestive and arthritic diseases, was associated with a significantly increased risk of healthcare utilization and health expenditures. The findings may help in planning future healthcare and managing multimorbidity more effectively.

1. Introduction

The global population is ageing rapidly, posing new and pressing challenges to most countries' healthcare systems, including China (Wang and Chen, 2014). Chronic diseases are a significant contributor to disparities in healthcare outcomes and economic burdens (Wang et al., 2005). Previous research demonstrated a significant association between the number of chronic diseases, healthcare utilization, and health expenditures (Chen et al., 2018a; Lehnert et al., 2011; Palladino et al., 2016; Sum et al., 2018). As people are living longer and exposed to more risk factors, the prevalence of multimorbidities, defined as the concurrence of at least two chronic diseases in an individual (World Health Organization (WHO), 2008), is increasing in many countries (Barnett et al., 2012), and affects nearly 50 % of middle-aged and older Chinese adults (Yao et al., 2019). Older people with multimorbidities impose a complex demand on healthcare systems as they require more frequent

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https://doi.org/10.1016/j.jad.2023.02.135
Received 18 October 2022; Received in revised form 22 February 2023; Accepted 24 February 2023
Available online 2 March 2023

health services (Bähler et al., 2015), leading to increased healthcare expenses (Bähler et al., 2015) and a higher risk of catastrophic expenditures for families (McRae et al., 2013). Multimorbidity is considered a major cause of healthcare inefficiency since it increases the likelihood of unnecessary inpatient admission, inefficient disease management, insufficient therapy, and communication obstacles (Glynn et al., 2011; World Health Organization (WHO), 2008). These have resulted in an unavoidable increase in the number of older adults with unmet healthcare needs, as the present infrastructure and healthcare systems are not built to satisfy their needs (Taylor et al., 2009). Multimorbidity is one of the most pressing issues in healthcare, both in China and worldwide (Barnett et al., 2012; Marengoni et al., 2011). To fully understand the healthcare challenges associated with multimorbidity, it is crucial to examine its impact on healthcare utilization and health expenditures thoroughly.

Previous studies on the relationship between multimorbidity, healthcare utilization, and health expenditures had limitations. One limitation is that most studies examined multimorbidity as a binary variable or by counting the number of chronic conditions (Lehnert et al., 2011; Marengoni et al., 2011; Wang et al., 2015; Zhao et al., 2021), which may not accurately reflect the specific combinations or patterns of chronic conditions. To address this, some researchers have attempted to identify different patterns of chronic diseases and their impact on healthcare utilization and health expenditures (Buja et al., 2018; Dong et al., 2013; Juul-Larsen et al., 2020; Olaya et al., 2017; Teh et al., 2018; Zhai et al., 2023). For example, Olaya et al. used latent class analysis (LCA) to identify multimorbidity patterns and discovered two multimorbidity patterns ("cardiovascular/mental/arthritis" and "metabolic/stroke") strongly linked to increased healthcare utilization (Olaya et al., 2017). Another limitation of previous studies is that they were primarily focused on older adults and ignored the middle-aged population (Chen et al., 2018b; Glynn et al., 2011; Marengoni et al., 2011; Palladino et al., 2016), even though chronic diseases often begin in middle age due to long-term exposure to risk factors. Additionally, many studies used cross-sectional data to explore the influence of multimorbidity on healthcare utilization and health expenditures (Chen et al., 2018a, 2018b), leaving the developmental trajectories of multimorbidity and its impact on healthcare utilization and health expenditures largely unknown.

With the aim of addressing the limitations of previous research in this field, this study utilized a national longitudinal survey database to (1) uncover the multimorbidity trajectory groups among middle-aged and older adults experiencing new-onset multimorbidity and (2) investigate the association between multimorbidity trajectories, healthcare utilization, and health expenditures.

2. Methods

2.1. Data source

The present study utilized data collected from three waves of the China Health and Retirement Longitudinal Study (CHARLS), with a follow-up of the 2011 baseline sample in 2013 and again in 2015. The CHARLS is a nationally representative longitudinal survey of middle-aged and older Chinese adults that aims to provide a high-quality nationally representative sample of Chinese residents' data to serve the needs of scientific research on health, economic position, and quality of life as people age. This study used a multistage, stratified probability-proportionate-to-size design to gather data from a nationally representative sample of Chinese residents aged 45 and older from 150 counties/districts and 450 villages/resident committees throughout 28 provinces in China. The CHARLS collected high-quality data through face-to-face interviews with a structured questionnaire. The CHARLS questionnaire includes demographics, family structure and connections, health status and functioning, cognition, financial and housing wealth, income and expenses, job status and history, biomarkers, healthcare utilization, and insurance. The questionnaire is reviewed and tested carefully to ensure clarity, accuracy, and effectiveness, and took into account factors such as cultural background and education level of the respondents. The original study included detailed descriptions of the survey design and processes (Zhao et al., 2014). The study was authorized by Beijing University's Biomedical Ethics Committee, and all subjects provided informed consent.

The baseline survey included 17,708 individuals from 10,257 households (overall response rate: 80.5 %), of whom 15,186 were re-investigated in wave 2 (in 2013) and 13,565 in wave 3 (in 2015). Participants were excluded from the analysis if they: 1) had one or more missing values in chronic conditions ($n = 4741$), 2) were younger than 45 years ($n = 244$), and 3) had multimorbidities ($\geq$2 chronic conditions) at baseline ($n = 3032$). Finally, a total of 5548 participants were left for the current analysis. Fig. 1 depicts a flowchart of participant selection.

2.2. Measures

2.2.1. Chronic conditions and multimorbidities

Based on the availability of the CHARLS data, 14 self-reported chronic diseases were utilized to measure multimorbidity, including hypertension, dyslipidemia, diabetes, cancer, chronic lung diseases, liver disease, heart disease, stroke, kidney disease, stomach disease, emotional problems, memory-related diseases, arthritis, and asthma. Multimorbidity was defined as the presence of two or more of the above-mentioned chronic conditions (Barnett et al., 2012). Participants who did not have multimorbidities at the baseline survey but were diagnosed with multimorbidities in any of the subsequent follow-up waves were considered to have new-onset multimorbidity.

2.2.2. Healthcare utilization and health expenditures

Three dimensions of healthcare utilization were analyzed in this study: outpatient visits, inpatient visits, and unmet healthcare needs. The first two dimensions were measured by asking the respondents whether they had received any outpatient care in the past month or inpatient care in the last year. If they replied "yes" to these questions, they were then asked how many trips they had made to outpatient care in the past month or inpatient care in the past year. Unmet healthcare needs were evaluated based on whether the participants reported having unmet needs for either outpatient or inpatient care. Participants had an unmet need for outpatient care if they had been sick the previous month, but had not visited any medical facilities or walk-in medical services. Participants had an unmet need for inpatient care if their doctor had advised them to be hospitalized but they did not get inpatient care in the past year. The study also analyzed health expenditures, including healthcare costs and catastrophic health expenditures (CHE). Healthcare costs included what the participants paid in total and for out-of-pocket expenditures (OOPEs) (deducting the reimbursed expenses) for outpatient care during the last month and inpatient care during the last year. We categorized a household as having catastrophic health expenditures when the out-of-pocket spending on health was $\geq$40 % of the household's capacity to pay (Cylus et al., 2018). Details on unmet healthcare needs (Gao et al., 2021), healthcare costs (Zhao et al., 2021), and catastrophic health expenditures (Zhao et al., 2020) have been previously documented.

2.2.3. Covariates

The following variables were included as covariates in the current analyses: age (45–59, 60+ years), sex (male, female), self-rated health (poor, fair, good), education (no formal education, primary school, middle school or above), body mass index (BMI) (underweight: <18.5 kg/m^2, normal: 18.5–22.9 kg/m^2, overweight: 23.0–27.4 kg/m^2, obese: $\geq$27.5 kg/m^2) (Nishida, 2004), occupation (agricultural, non-agricultural, unemployed/retired), ever smoker (no, yes), alcohol drinker (no, yes), exercise status (no, yes), marital status (married/cohabitation, single: divorced, separated, widowed, or never married),

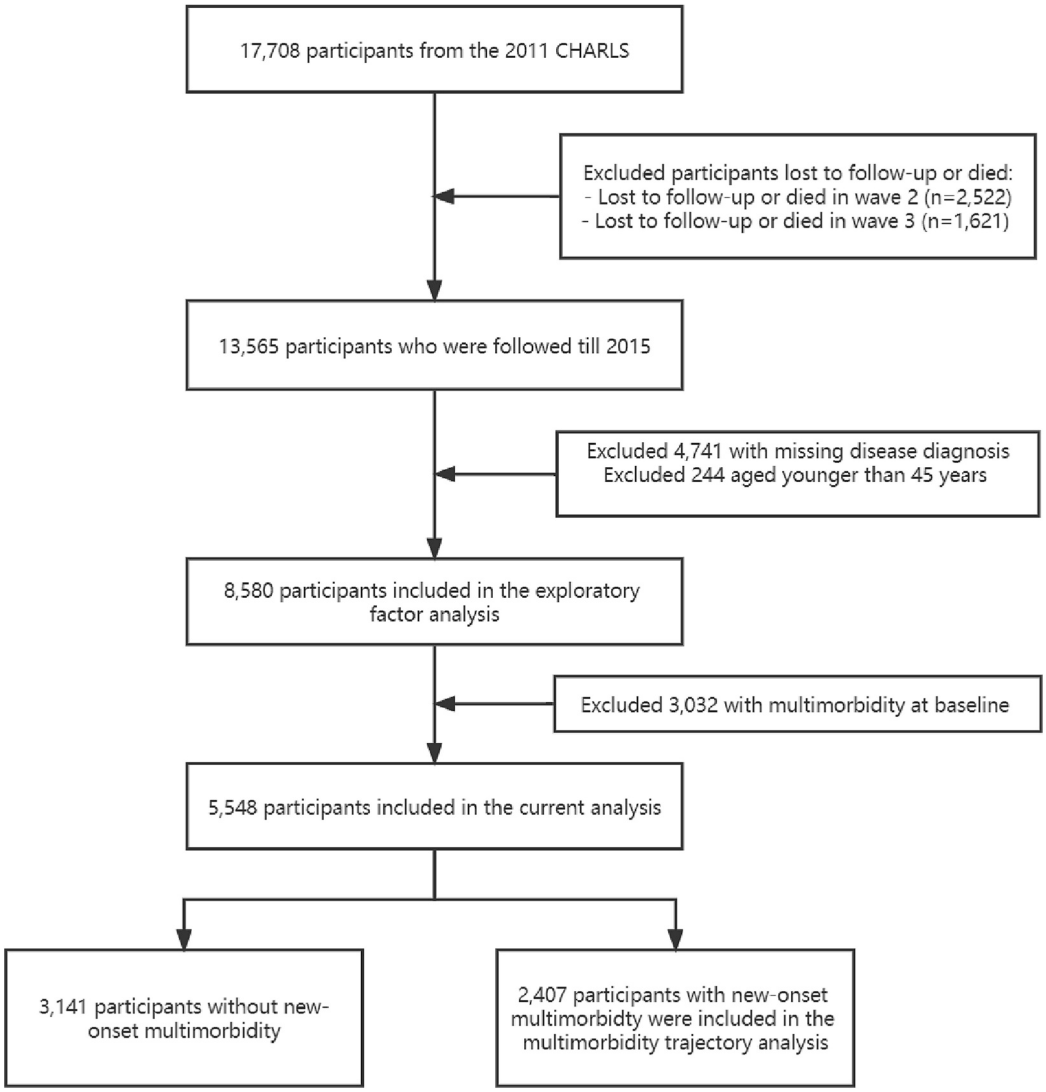

Fig. 1. Flow chart of sample selection for the current analysis.

annual household expenditures (total household per capita consumption) categorized into quartiles, social participation (whether the respondent participated in any social activities), location of residence (rural, urban), and health insurance status (no medical insurance, public health insurance, private health insurance, other medical insurance).

2.3. Statistical analyses

First, an exploratory factor analysis (EFA) was applied to determine how chronic conditions that displayed multimorbidity patterns tended to group together. Given the categorical characteristics of the variables, we used the weighted least squares means and variance (WLSMV) estimator to extract the factors (Muthén, 1984). Multimorbidity patterns were determined based on model fit metrics and their interpretability. Four fit statistics were used to assess the goodness of fit: root mean squared error of approximation (RMSEA), comparative fit index (CFI), the Tucker-Lewis index (TLI), and standardized root mean square residual (SRMR). A good model fit was defined as CFI and TLI values $>$ 0.95 and SRMR and RMSEA values $<$ 0.06 (Brown, 2006; West et al., 2012). The factor-loading matrices were obliquely rotated to improve interpretability. A factor loading of $\geq$0.40 indicated a strong association between the chronic condition and the latent multimorbidity pattern. Each participant's composite factor scores for each detected multimorbidity pattern were calculated at each wave by multiplying the relevant factor-loading and chronic conditions, with a higher score indicating more conditions loaded onto the specific multimorbidity pattern. In this study, we performed EFA using baseline data, excluding chronic conditions with a prevalence of $<$1.0 % to enhance the robustness of the analysis (Yao et al., 2020a). Factor scores for each wave were calculated using factor loadings from the baseline data to make the factor scores comparable across waves.

Then, group-based multi-trajectory modeling (GBMTM) was employed to identify subgroups of participants with similar joint trajectories based on the scores of the multimorbidity patterns (Nagin, 2005; Nagin et al., 2018). The factor scores of each multimorbidity pattern over the three waves of CHARLS were used as outcome variables in this model and were modeled using a censored normal distribution, with the lowest score ($-$0.31) as the censored minimum and the highest score (2.58) as the censored maximum. Model fitting was performed iteratively by comparing models with varying numbers of groups (1–6) and trajectory shapes (linear, quadratic, and cubic). Model selection was based on the Bayesian information criterion (BIC) and Akaike's information criterion (AIC) values, with preference given to the model with the lowest BIC and AIC values. Additionally, the proportion assigned to each trajectory group, based on the maximum posterior probability rule, should be $>$5 %, and the average posterior probability of group membership should be at least 0.7. The final model should also be clinically relevant and interpretable. Details on GBMTM, including the criteria for selecting a final model, appear in previous studies (Nagin, 2005; Nagin et al., 2018).

Finally, random-effects logistic regression, random-effects negative binomial regression models, and generalized linear regression models (GLM) were applied to investigate the associations between multimorbidity trajectories, healthcare utilization, and health expenditures. The random-effects logistic regression model was employed to analyze outpatient care, inpatient care, unmet healthcare needs, and catastrophic health expenditures. Meanwhile, the number of outpatient and inpatient visits was analyzed using the random-effects negative binomial regression model (Zhao et al., 2020). The generalized linear regression models with log link and gamma distribution was applied to estimate the association of multimorbidity trajectories with total health expenditures and OOPEs for outpatient and inpatient care (Zhao et al., 2021). For GLM analysis, random-effects logistic regression, and negative binomial regression analysis, the coefficient, odds ratios (ORs) and incidence rate ratios (IRRs), and their 95 % confidence intervals (CIs) were reported, respectively. All models were adjusted for time and the covariates mentioned above.

EFA analyses were performed using Mplus, version 8.0, and GBMTM, and other analyses were performed using Stata, version 16.0 (StataCorp, College Station, TX). A two-sided *P*-value of <0.05 was considered statistically significant.

2.4. Sensitivity analyses

A series of sensitivity analyses were conducted to assess the robustness of the results. Firstly, two EFA were conducted using cross-sectional data from the 2013 and 2015 CHARLS waves to evaluate the stability of the EFA results. The same set of chronic conditions as those at baseline was included to ensure comparability with the main analysis. Secondly, we limited the sample to participants with complete data for at least two waves (n = 6576) to examine the impact of incomplete data on trajectory analysis. Finally, we compared the characteristics of the samples with and without participants who were excluded during the sample selection process and analyzed the relationship between multimorbidity, healthcare utilization, and health expenditures among those who were excluded from the current analysis to estimate the effect of the exclusions.

3. Results

3.1. Baseline characteristics

In the current analysis, 2407 (43.39 %) of the 5548 participants developed multimorbidities during the follow-up period. Supplementary Table 1 provides a detailed breakdown of the sample characteristics and highlights the differences between those with and without new-onset multimorbidity. Briefly, compared to individuals without multimorbidities, those with new-onset multimorbidity were more likely to be female, report fair or poor health, have a BMI of 27.5 kg/m^2 or greater, be unemployed or retired, utilize both outpatient and inpatient care services, incur higher healthcare costs, have no formal education, and experience unmet needs for both outpatient and inpatient care.

3.2. Exploratory factor analysis of latent multimorbidity patterns

In our study, which included 14 conditions, cancer, with a prevalence of <1 %, was excluded from the factor analysis (as shown in Table 1). Our analysis revealed four distinct multimorbidity patterns: 1) a cardiometabolic pattern that was strongly correlated with heart disease, hypertension, diabetes, and dyslipidemia; 2) a brain pattern, associated with stroke, memory-related diseases, and emotional problems; 3) a digestive-arthritic pattern, characterized by high correlations with kidney disease, liver disease, digestive disease, and arthritis; and 4) a respiratory pattern with strong associations with chronic lung diseases and asthma.

Table 1
Factor loadings of the four multimorbidity patterns identified by the exploratory factor analysis.

Chronic conditions	Cardio-metabolic pattern	Brain pattern	Digestive-arthritic pattern	Respiratory pattern
Dyslipidemia	**0.75**	−0.01	0.09	−0.04
Diabetes	**0.68**	−0.04	−0.04	0.08
Hypertension	**0.56**	0.28	−0.01	−0.01
Heart disease	0.39	0.23	0.34	0.05
Stroke	0.23	**0.43**	−0.01	−0.04
Memory-related diseases	0.04	**0.69**	−0.01	−0.04
Emotional problems	−0.25	**0.53**	0.03	0.06
Stomach disease	0.00	−0.19	**0.72**	−0.03
Arthritis	0.03	0.03	**0.46**	0.03
Liver disease	−0.01	0.02	**0.40**	0.00
Kidney disease	0.00	0.18	0.38	0.02
Chronic lung diseases	−0.05	0.09	0.13	**0.66**
Asthma	0.04	−0.03	−0.03	**1.10**

Notes: Factor loadings indicate the strength of association between each chronic condition and each latent multimorbidity pattern, with a factor loading of $\geq$0.4 indicated in bold.

3.3. Group-based multi-trajectory modeling of multimorbidity trajectories

We identified three distinct multimorbidity trajectory groups among the participants with new-onset multimorbidity based on the four latent multimorbidity pattern scores (as shown in Fig. 2). The resulting trajectory groups were named to reflect the dominant increasing trends in the multimorbidity pattern scores. Specifically, the first group was named the "digestive-arthritic" trajectory (N = 1377, 57.21 %) due to its prominent increasing trend in digestive-arthritic multimorbidity pattern scores. Similarly, the second group was named the "cardiometabolic/brain" trajectory (N = 834, 34.65 %), and the third group was named the "respiratory/digestive-arthritic" trajectory (N = 196, 8.14 %). These trajectory groups represented the growth of different multimorbidity patterns from no multimorbidity to multimorbidities.

3.4. Baseline characteristics associated with multimorbidity trajectories

The baseline characteristics of the participants in each multimorbidity trajectory group are presented in Table 2 and Supplementary Table 2. There were significant differences in factors, such as sex, age, self-rated health, education, BMI, occupation, ever-smoker, residence location, utilization of outpatient and inpatient care services, unmet outpatient and inpatient care needs, healthcare costs, and catastrophic health expenditures among the multimorbidity trajectory groups. Notably, participants in the digestive-arthritic trajectory were more likely to be female and face catastrophic health expenditures. Those in the cardiometabolic/brain trajectory tended to have a higher BMI and incur higher healthcare costs. Participants in the respiratory/digestive-arthritic trajectory were inclined to be smokers, report poor self-rated health, and have unmet healthcare needs.

3.5. Association between multimorbidity trajectories, healthcare utilization, and health expenditures

The results of the analysis of the associations between multimorbidity trajectory groups, healthcare utilization, and health expenditures are presented in Tables 3 and 4, respectively. Controlling for time and the mentioned covariates, we used participants without

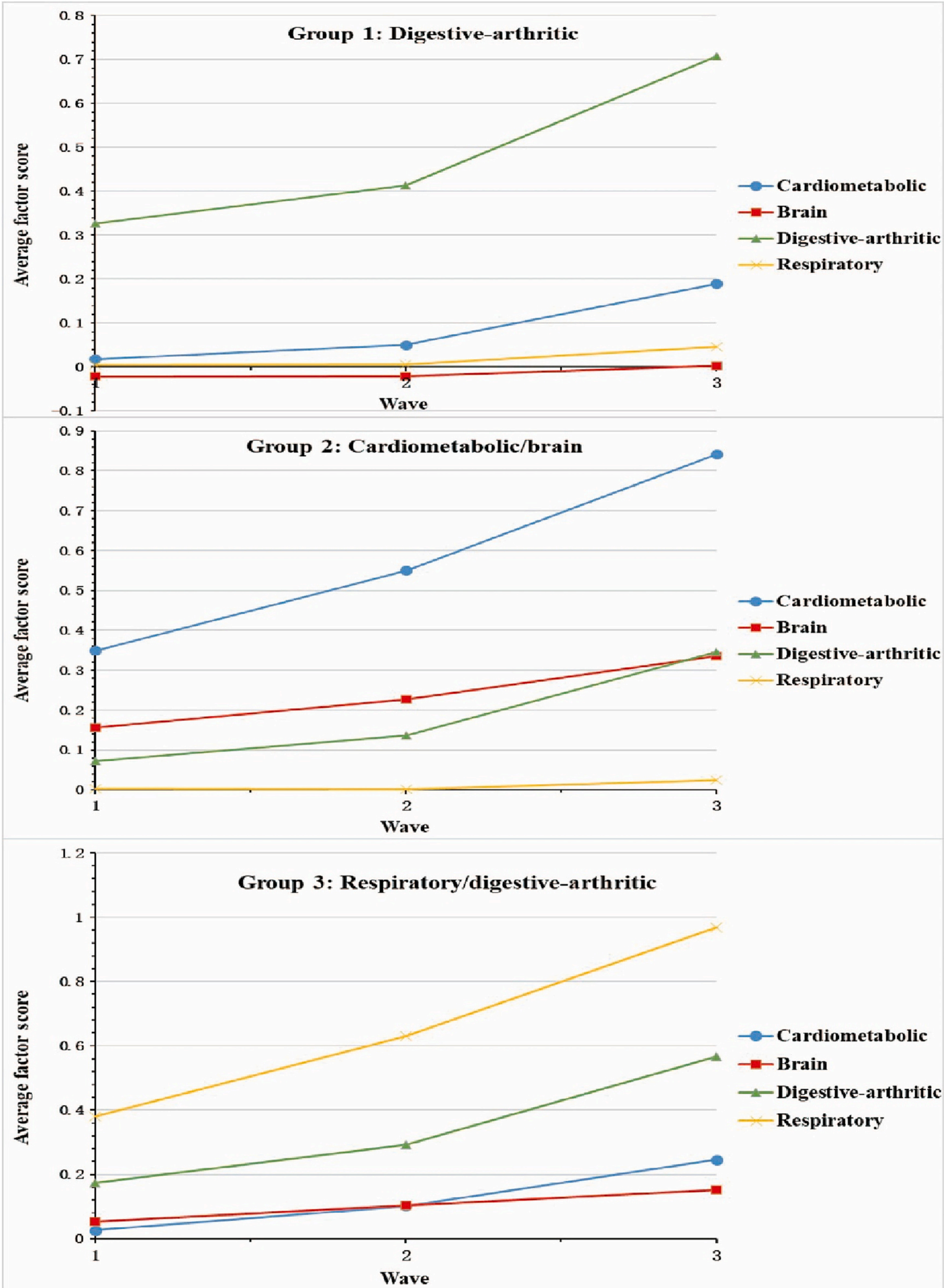

Fig. 2. Average factor scores for each multimorbidity trajectory group in middle-aged and older adults.

multimorbidities as the reference group. Our results indicated that those who developed multimorbidities were at a significantly increased risk of utilizing all dimensions of healthcare and incurring greater health expenditures. All multimorbidity trajectory groups showed a higher risk of utilizing outpatient and inpatient care, reporting unmet healthcare needs, and incurring higher healthcare costs. The digestive-arthritic trajectory group tended to make trips to both outpatient and inpatient care services (number of outpatient visits: IRR = 1.68, 95%CI: 1.37–2.07; number of inpatient visits: IRR = 1.72, 95%CI: 1.26–2.34), incur out-of-pocket expenditures for both outpatient and inpatient care (outpatient: coefficient = 0.78, 95%CI: 0.37–1.19; inpatient: coefficient = 0.81, 95%CI: 0.23–1.39), and have a higher likelihood of incurring catastrophic health expenditures (OR = 1.70, 95%CI: 1.03–2.81). In contrast, participants in the cardiometabolic/brain trajectory group were more likely to seek inpatient care (OR = 2.30, 95%CI: 1.51–3.51), report unmet inpatient care needs (OR = 4.35, 95%CI: 2.09–9.05), and

Table 2
The distribution of healthcare utilization and health expenditures according to multimorbidity trajectory groups.

Characteristic	No multimorbidity (N = 3141)	Digestive-arthritic (N = 1379)	Cardiometabolic/brain (N = 831)	Respiratory/digestive-arthritic (N = 197)	*P* value
Outpatient care, n (%)[a]					<0.001
No	2797 (89.6)	1119 (82.5)	700 (85.2)	159 (83.2)	
Yes	325 (10.4)	238 (17.5)	122 (14.8)	32 (16.8)	
Number of outpatient visits, mean ± SD[b]	0.2 ± 1.0	0.4 ± 1.1	0.3 ± 1.3	0.4 ± 1.1	<0.001
Inpatient care, n (%)[a]					<0.001
No	3012 (96.0)	1286 (93.4)	769 (92.3)	186 (94.9)	
Yes	127 (4.0)	91 (6.6)	64 (7.7)	10 (5.1)	
Number of inpatient visits, mean ± SD[b]	0.1 ± 0.5	0.1 ± 0.4	0.1 ± 0.4	0.1 ± 0.2	<0.001
Unmet outpatient care needs, n (%)[a]					<0.001
No	2716 (95.5)	1050 (91.4)	684 (95.9)	144 (88.9)	
Yes	128 (4.5)	99 (8.6)	29 (4.1)	18 (11.1)	
Unmet inpatient care needs, n (%)[a]					<0.001
No	2967 (98.8)	1234 (97.2)	779 (97.5)	170 (97.1)	
Yes	36 (1.2)	35 (2.8)	20 (2.5)	5 (2.9)	
OOPE for outpatient care (yuan), mean ± SD[b]	50.6 ± 554.3	82.8 ± 1152.1	273.4 ± 5970.3	52.1 ± 306.4	<0.001
OOPE for inpatient care (yuan), mean ± SD[b]	150.1 ± 1298.1	453.5 ± 4339.0	645.2 ± 7706.0	152.0 ± 770.7	<0.001
Total health expenditures (yuan), mean ± SD[b]	986.0 ± 8557.4	1813.6 ± 19,113.4	4624.4 ± 84,517.0	957.6 ± 3972.0	<0.001
Catastrophic health expenditures, n (%)[a]					<0.001
No	2712 (98.7)	1190 (97.5)	739 (98.7)	171 (99.4)	
Yes	37 (1.3)	30 (2.5)	10 (1.3)	1 (0.6)	

[a] Pearson chi-square tests for categorical variables.
[b] One-way analysis of variance tests for continuous variables.

Table 3
The association of multimorbidity trajectories and healthcare utilization among Chinese middle age and older adults.

Trajectory group	Outpatient care	Inpatient care	Number of outpatient visits	Number of inpatient visits	Unmet outpatient care needs	Unmet inpatient care needs
	OR (95 % CI)	OR (95 % CI)	IRR (95 % CI)	IRR (95 % CI)	OR (95 % CI)	OR (95 % CI)
No multimorbidity (referent)	1.00	1.00	1.00	1.00	1.00	1.00
New-onset multimorbidity	1.78*** (1.44–2.21)	2.08*** (1.50–2.87)	1.63***(1.36–1.96)	1.83***(1.39–2.40)	1.67**(1.22–2.29)	3.23***(1.77–5.90)
Digestive-arthritic	1.85*** (1.45–2.36)	1.92*** (1.33–2.77)	1.68***(1.37–2.07)	1.72***(1.26–2.34)	1.85***(1.31–2.62)	2.56**(1.33–4.92)
Cardiometabolic/brain	1.61** (1.20–2.17)	2.30*** (1.51–3.51)	1.51**(1.17–1.94)	1.98***(1.39–2.81)	1.19(0.75–1.90)	4.35***(2.09–9.05)
Respiratory/digestive-arthritic	2.05** (1.22–3.47)	2.25*(1.08–4.69)	1.81**(1.17–2.78)	1.98*(1.09–3.60)	2.52*(1.21–5.24)	3.75*(1.17–12.08)

Notes: All models controlled for time, age, gender, marital status, living area, occupation, self-rated health, BMI, ever-smoker, alcohol drinker, exercise status, annual household expenditures, social participation, and health insurance status.
Abbreviations: CI, confidence interval; OR, odds ratio; IRR, incidence rate ratio.
*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.

Table 4
The association of multimorbidity trajectories and health expenditures among Chinese middle age and older adults.

Trajectory group	OOPE for outpatient care	OOPE for inpatient care	Total health expenditures	Catastrophic health expenditures
	Coefficient (95 % CI)	Coefficient (95 % CI)	Coefficient (95 % CI)	OR (95 % CI)
No multimorbidity (referent)	1.00	1.00	1.00	1.00
New-onset multimorbidity	0.88***(0.53–1.24)	0.64*(0.14–1.13)	0.72***(0.39–1.04)	1.69*(1.08–2.64)
Digestive-arthritic	0.78***(0.37–1.19)	0.81**(0.23–1.39)	0.59**(0.24–0.95)	1.70*(1.03–2.81)
Cardiometabolic/brain	1.11***(0.62–1.60)	0.49(−0.14–1.12)	0.94***(0.47–1.40)	1.66(0.93–2.97)
Respiratory/digestive-arthritic	0.70*(0.03–1.36)	−0.11(−1.10–0.89)	0.56(−0.04–1.16)	1.78(0.69–4.61)

Notes: All models controlled for time, age, gender, marital status, living area, occupation, self-rated health, BMI, ever-smoker, alcohol drinker, exercise status, annual household expenditures, social participation, and health insurance status.
Abbreviations: CI, confidence interval; OOPE, out-of-pocket expenditure; OR, odds ratio.
*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.

incur higher total health expenditures (coefficient = 0.94, 95%CI: 0.47–1.40). Lastly, the respiratory/digestive-arthritic trajectory group was more inclined to utilize outpatient care (OR = 2.05, 95%CI: 1.22–3.47) and experience unmet outpatient care needs (OR = 2.52, 95%CI: 1.21–5.24).

3.6. Sensitivity analyses

We found consistent patterns in the cross-sectional data from the 2013 and 2015 CHARLS waves (as shown in Supplemental Tables 3 and 4), indicating the robustness of the EFA. In a sensitivity analysis with participants who had complete data from at least two waves, the multimorbidity trajectories remained consistent with the results of the main analysis (as shown in Supplemental Fig. 1). Participants who were excluded from the analysis were more likely to be female, older, overweight or obese, unemployed or retired, single, have no formal education, report poorer self-rated health, and have higher healthcare costs, unmet outpatient and inpatient care needs, catastrophic health expenditures, and utilize both inpatient and outpatient care services (as shown in Supplemental Table 5). The results from the sensitivity analysis showed that participants with multimorbidities had a significantly increased risk of utilization and expenditures in all dimensions of healthcare compared to those without multimorbidities (as shown in Supplemental Tables 6 and 7).

4. Discussion

We investigated joint developmental multimorbidity trajectories among middle-aged and older adults through a comprehensive study of a large, nationally representative sample of Chinese adults. Three distinct multimorbidity trajectories were identified according to the latent patterns of chronic conditions with prominent increases and were named "digestive-arthritic," "cardiometabolic/brain," and "respiratory/digestive-arthritic" trajectories. Compared to those without multimorbidities, all multimorbidity trajectory groups experienced a significant increase in outpatient and inpatient care, unmet healthcare needs, and healthcare costs. Notably, only the digestive-arthritic trajectory group was linked to a higher risk of catastrophic health expenditures. The insights gained from this study highlight the need for greater attention and resources to be directed toward improving the healthcare system's ability to manage multimorbidities effectively.

Our study revealed multimorbidity patterns similar to previous research (Yao et al., 2020b), suggesting that shared underlying factors and disease processes may be involved (Prados-Torres et al., 2014; Yao et al., 2019; Zhang et al., 2019). The cardiometabolic pattern and its potential causes were documented in previous studies (Prados-Torres et al., 2014). With regard to the respiratory pattern, our findings are consistent with prior research that showed a strong association between asthma and an increased risk of chronic lung diseases (Silva et al., 2004). A limited body of evidence suggested a positive correlation between emotional problems and memory-related diseases, which were included in the brain pattern seen in this study (Busija et al., 2019). Consistent with previous findings, we also established a close relationship between kidney diseases, liver diseases, digestive diseases, and arthritis, which comprised the digestive-arthritic pattern (Kochi et al., 2018; Musso et al., 2014).

Previous studies investigated the impact of multimorbidities on healthcare utilization and health expenditures using CHARLS longitudinal data (Zhao et al., 2020; Zhao et al., 2021). Zhao et al. analyzed the relationship between physical-mental multimorbidities, healthcare utilization, and health spending in 2011 and 2015 CHARLS data. They classified multimorbidities into two categories: physical multimorbidities and physical-mental multimorbidities, and found that individuals with physical-mental multimorbidities had higher utilization of healthcare services and incurred higher OOPEs compared to those with single or physical multimorbidities (Zhao et al., 2021). In another study, using data from three waves of CHARLS (2011–2015), researchers included 11 physical diseases to assess physical multimorbidities and their impact on health service use and CHE in different socioeconomic groups. The results showed that physical multimorbidities were associated with the increased use of healthcare services and a higher risk of CHE (Zhao et al., 2020). Our study, which used similar data and statistical methods, found that new-onset multimorbidity was associated with the increased utilization of healthcare services, higher OOPEs for both outpatient and inpatient care, and an increased likelihood of incurring CHE. However, our study went further by exploring the impact of different multimorbidity patterns on healthcare utilization and health expenditures, and categorized the development of multimorbidity patterns into three distinct trajectories among individuals with new-onset multimorbidity.

Some research has explored the link between multimorbidity patterns, healthcare utilization, and health expenditures (Buja et al., 2018; Dong et al., 2013; Juul-Larsen et al., 2020; Olaya et al., 2017; Teh et al., 2018; Zhai et al., 2023). For instance, Huan-Ji Dong et al. identified five multimorbidity clusters and found that clusters consisting of cardiac and pulmonary conditions were more strongly related to hospitalization than single diseases (Dong et al., 2013). Zhai et al. conducted a study on Chinese individuals aged 60 years or older living alone and identified four multimorbidity patterns through latent class analysis, finding that the "cardiovascular" and "multisystem" patterns were associated with a higher risk of CHE compared to the "minimal disease" pattern (Zhai et al., 2023). However, these previous studies had limitations, such as only examining adults who were over 80 years old (Dong et al., 2013; Teh et al., 2018), living alone (Zhai et al., 2023), or hospitalized (Buja et al., 2018; Juul-Larsen et al., 2020), which limits their external validity. They also did not consider the progression and impact of multimorbidities over time. Our study fills the gap by modeling the joint trajectories of latent factor scores underlying chronic diseases based on a nationally representative sample, providing new insight into the dynamic accumulation of multimorbidities and their impact on healthcare utilization and health expenditures.

Previous research demonstrated that "cardiorespiratory/mental/arthritis" and "metabolic/stroke" clusters were associated with more healthcare visits and a higher risk of hospitalization (Olaya et al., 2017). Our study found similar results, with higher utilization of outpatient and inpatient care in the digestive-arthritic and cardiometabolic/brain trajectory groups. Our study also found that the digestive-arthritic trajectory group was more likely to incur catastrophic health expenditures, possibly due to increased trips for outpatient and inpatient care and higher OOPEs for outpatient and inpatient healthcare. The findings of our study are consistent with previous research that showed that patients with multimorbidities were more likely to report unmet healthcare needs (Gao et al., 2021). Our study also found a significantly increased risk of unmet healthcare needs among middle-aged and older adults with an increasing burden of chronic lung diseases and asthma.

People with multiple chronic conditions face greater clinical demands compared to those with only one, leading to problems when healthcare focuses on specific diseases rather than individuals. The implementation of various disease-specific recommendations in patients with multimorbidities can result in clinical chaos, overmedication, and conflicting treatments for individual diseases (Hughes et al., 2013), leading to fragmented, costly, and possibly ineffective, or even harmful, care (Sturmberg et al., 2017). Our findings provide new evidence to support the development of targeted policies and interventions to address the growing burden of multimorbidities in China. To better manage multimorbidities, healthcare systems must move away from single-disease models and adopt integrated care models (Hopman et al., 2016; Lehnert et al., 2011; Sturmberg et al., 2017), such as the "People-centered Integrated Care" program (the "Luohu model") in China, which promotes the holistic management of chronic disease patients by general practitioners (Wang et al., 2018; Wei et al., 2015). Our research also highlights the increased healthcare utilization and health expenditures associated with the growing burdens of multimorbidities, particularly the multimorbidities of digestive and arthritic diseases, emphasizing the need for expanded insurance coverage and improved benefits packages for patients with these chronic conditions in China.

The current study estimated the multimorbidity trajectory of middle-aged and older adults in a longitudinal, large-scale, nationally representative sample of the Chinese population that gives solid estimates of essential variables using the GBMTM method, which accounted for the co-development of multimorbidity patterns and provided a greater understanding of the complexity of multimorbidity accumulation. Our findings hold the potential to inform policymakers on the significance and characteristics of multimorbidities in China.

Our research had several limitations. Firstly, the use of self-reported measures for chronic diseases and healthcare utilization and expenditures may have led to an underestimation of their prevalence, especially among older individuals and those from lower socioeconomic and educational backgrounds who were more likely to under-report such information (Fortin et al., 2012). Additionally, the absence of an electronic medical record system in China resulted in the lack of a criterion standard for stringent validation, which increased the possibility of underdiagnosis or misclassification of diseases. However, prior research showed that respondents' self-reported data on chronic diseases had a high level of agreement with information from their medical records (Kriegsman et al., 1996). Secondly, the CHARLS questionnaire did not inquire about all chronic conditions typically included in clinical database research. Further research is required to understand the impact of multimorbidities caused by other prevalent chronic diseases, such as gout and osteoporosis. Thirdly, the study only adjusted for individual socio-demographic characteristics and did not consider supply-side factors, such as hospital bed availability and primary care physician availability. Fourthly, the results of the study were not free from selection bias and attrition effects, as only respondents who participated in all three data collection waves were included. The participants included in the analysis were healthier than those who were not, so the results should be interpreted with caution, taking sample characteristics and the possibility of selection bias into account. Finally, the financing and management of healthcare in China may limit the generalizability of the findings as other countries may have different social or healthcare policies that influence public resource priorities and address inequities related to healthcare utilization.

5. Conclusion

The development of multimorbidities among middle-aged and older adults in China showed great heterogeneity. Compared to individuals who did not develop multimorbidities, all trajectory groups had a significantly elevated risk of outpatient and inpatient care, unmet healthcare needs, and increased healthcare costs. Of particular note, participants with digestive-arthritic trajectories had a significantly higher risk of incurring catastrophic health expenditures. These findings have the potential to inform the alignment of existing plans and prioritize health services in preparation for the growing issue of multimorbidities.

Abbreviations

CHARLS	China Health and Retirement Longitudinal Study
BIC	Bayesian information criterion
AIC	Akaike's information criterion
EFA	exploratory factor analysis
GBMTM	group-based multi-trajectory modeling
WLSMV	weighted least squares means and variance
CFI	Comparative fit index
TLI	Tucker and Lewis index
RMSEA	root mean squared error of approximation
SRMR	standardized root mean square residual
CHE	catastrophic health expenditures
LCA	latent class analysis
OOPE	out-of-pocket expenditure
GLM	generalized linear regression model
CI	confidence interval
OR	odds ratio
IRR	incidence rate ratio

Funding

This work was supported by the National Natural Science Foundation of China (Grant number 81973144) and the Natural Science Foundation of Xiamen (Grant number 3502Z20227014). The funding body had no role in the design of the study and collection, analysis, and interpretation of data and in writing the manuscript.

CRediT authorship contribution statement

Zeyun Zhang: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Visualization. **Manqiong Yuan:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Kanglin Shi:** Formal analysis, Data curation, Writing – review & editing. **Chuanhai Xu:** Data curation, Writing – review & editing. **Jianlin Lin:** Data curation, Writing – review & editing. **Zaixing Shi:** Conceptualization, Methodology, Writing – review & editing. **Ya Fang:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition.

Conflict of interest

All authors declare that they have no conflicts of interest.

Acknowledgments

The authors would like to thank China Health and Retirement Longitudinal Study participants and researchers for their contributions to this important study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2023.02.135.

References

Bähler, C., Huber, C.A., Brüngger, B., Reich, O., 2015. Multimorbidity, health care utilization and costs in an elderly community-dwelling population: a claims data based observational study. BMC Health Serv. Res. 15, 23. https://doi.org/10.1186/s12913-015-0698-2.

Barnett, K.N., Mercer, S.W., Norbury, M., Watt, G., Wyke, S., Guthrie, B., 2012. Epidemiology of multimorbidity and implications for health care, research, and medical education: a cross-sectional study. Lancet 380 (9836), 37–43. https://doi.org/10.1016/S0140-6736(12)60240-2.

Brown, T.A., 2006. Confirmatory Factor Analysis for Applied Research. Guilford Press, New York.

Buja, A., Rivera, M., De Battisti, E., Corti, M.C., Avossa, F., Schievano, E., et al., 2018. Multimorbidity and hospital admissions in high-need, high-cost elderly patients. J. Aging Health 32 (5–6), 259–268. https://doi.org/10.1177/0898264318817091.

Busija, L., Lim, K., Szoeke, C., Sanders, K.M., McCabe, M.P., 2019. Do replicable profiles of multimorbidity exist? Systematic review and synthesis. Eur. J. Epidemiol. 34 (11), 1025–1053. https://doi.org/10.1007/s10654-019-00568-5.

Chen, H., Chen, Y., Cui, B., 2018. The association of multimorbidity with healthcare expenditure among the elderly patients in Beijing, China. Arch. Gerontol. Geriatr. 79, 32–38. https://doi.org/10.1016/j.archger.2018.07.008.

Chen, H., Cheng, M., Zhuang, Y., Broad, J.B., 2018. Multimorbidity among middle aged and older persons in urban China: prevalence, characteristics and health service utilization. Geriatr Gerontol Int 18 (10), 1447–1452. https://doi.org/10.1111/ggi.13510.

Cylus, J., Thomson, S., Evetovits, T., 2018. Catastrophic health spending in Europe: equity and policy implications of different calculation methods. Bull. World Health Organ. 96 (9), 599–609. https://doi.org/10.2471/BLT.18.209031.

Dong, H.-J., Wressle, E., Marcusson, J., 2013. Multimorbidity patterns of and use of health services by Swedish 85-year-olds: an exploratory study. BMC Geriatr. 13, 120. https://doi.org/10.1186/1471-2318-13-120.

Fortin, M., Stewart, M., Poitras, M.-E., Almirall, J., Maddocks, H.L., 2012. A systematic review of prevalence studies on multimorbidity: toward a more uniform methodology. Ann. Fam. Med. 10 (2), 142–151. https://doi.org/10.1370/afm.1337.

Gao, Q., Prina, M.A., Wu, Y.-T., Mayston, R., 2021. Unmet healthcare needs among middle-aged and older adults in China. Age Ageing 51 (1), afab235. https://doi.org/10.1093/ageing/afab235.

Glynn, L.G., Valderas, J.M., Healy, P., Burke, E., Newell, J., Gillespie, P., et al., 2011. The prevalence of multimorbidity in primary care and its effect on health care utilization and cost. Fam. Pract. 28 (5), 516–523. https://doi.org/10.1093/fampra/cmr013.

Hopman, P., Heins, M.J., Korevaar, J.C., Rijken, M., Schellevis, F.G., 2016. Health care utilization of patients with multiple chronic diseases in the Netherlands: differences and underlying factors. Eur. J. Intern. Med. 35, 44–50. https://doi.org/10.1016/j.ejim.2016.08.025.

Hughes, L.D., Mcmurdo, M.E.T., Guthrie, B., 2013. Guidelines for people not for diseases: the challenges of applying UK clinical guidelines to people with multimorbidity. Age Ageing 42 (1), 62–69. https://doi.org/10.1093/ageing/afs100.

Juul-Larsen, H.G., Christensen, L.D., Bandholm, T., Andersen, O., Kallemose, T., Jørgensen, L.M., et al., 2020. Patterns of multimorbidity and differences in healthcare utilization and complexity among acutely hospitalized medical patients (≥65 years) – a latent class approach. Clin. Epidemiol. 12, 245–259. https://doi.org/10.2147/CLEP.S226586.

Kochi, M., Kohagura, K., Shiohira, Y., Iseki, K., Ohya, Y., 2018. Chronic kidney disease, inflammation, and cardiovascular disease risk in rheumatoid arthritis. J. Cardiol. 71 (3), 277–283. https://doi.org/10.1016/j.jjcc.2017.08.008.

Kriegsman, D.M.W., Penninx, B.W.J.H., van Eijk, J.T.M., Boeke, A.J.P., Deeg, D.J.H., 1996. Self-reports and general practitioner information on the presence of chronic diseases in community dwelling elderly. A study on the accuracy of patients' self-reports and on determinants of inaccuracy. J. Clin. Epidemiol. 49 (12), 1407–1417. https://doi.org/10.1016/s0895-4356(96)00274-0.

Lehnert, T., Heider, D., Leicht, H., Heinrich, S., Corrieri, S., Luppa, M., et al., 2011. Review: health care utilization and costs of elderly persons with multiple chronic conditions. Med. Care Res. Rev. 68 (4), 387–420. https://doi.org/10.1177/1077558711399580.

Marengoni, A., Angleman, S.B., Melis, R.J.F., Mangialasche, F., Karp, A., Garmén, A., et al., 2011. Aging with multimorbidity: a systematic review of the literature. Ageing Res. Rev. 10 (4), 430–439. https://doi.org/10.1016/j.arr.2011.03.003.

McRae, I., Yen, L.E., Jeon, Y.-H., Herath, P.M., Essue, B.M., 2013. Multimorbidity is associated with higher out-of-pocket spending: a study of older Australians with multiple chronic conditions. Austral. J. Prim. Health 19 (2), 144–149. https://doi.org/10.1071/Py12035.

Musso, G., Gambino, R., Tabibian, J.H., Ekstedt, M., Kechagias, S., Hamaguchi, M., et al., 2014. Association of non-alcoholic Fatty Liver Disease with chronic kidney disease: a systematic review and meta-analysis. PLoS Med. 11 (7), e1001680 https://doi.org/10.1371/journal.pmed.1001680.

Muthén, B., 1984. A general structural equation model with dichotomous, ordered categorical, and continuous latent variable indicators. Psychometrika 49 (1), 115–132. https://doi.org/10.1007/BF02294210.

Nagin, D.S., 2005. Group-based Modeling of Development. Harvard University Press, London.

Nagin, D.S., Jones, B.L., Passos, V.L., Tremblay, R.E., 2018. Group-based multi-trajectory modeling. Stat. Methods Med. Res. 27 (7), 2015–2023. https://doi.org/10.1177/0962280216673085.

Nishida, C., 2004. Appropriate body-mass index for Asian populations and its implications for policy and intervention strategies. Lancet 363 (9403), 157–163. https://doi.org/10.1016/S0140-6736(03)15268-3.

Olaya, B., Moneta, M.V., Caballero, F.F., Tyrovolas, S., Bayés, I., Ayuso-Mateos, J.L., et al., 2017. Latent class analysis of multimorbidity patterns and associated outcomes in Spanish older adults: a prospective cohort study. BMC Geriatr. 17, 186. https://doi.org/10.1186/s12877-017-0586-1.

Palladino, R., Tayu Lee, J., Ashworth, M., Triassi, M., Millett, C.J., 2016. Associations between multimorbidity, healthcare utilisation and health status: evidence from 16 European countries. Age Ageing 45 (3), 431–435. https://doi.org/10.1093/ageing/afw044.

Prados-Torres, A., Calderón-Larrañaga, A., Hancco-Saavedra, J., Poblador-Plou, B., van den Akker, M., 2014. Multimorbidity patterns: a systematic review. J. Clin. Epidemiol. 67 (3), 254–266. https://doi.org/10.1016/j.jclinepi.2013.09.021.

Silva, G.E., Sherrill, D.L., Guerra, S., Barbee, R.A., 2004. Asthma as a risk factor for COPD in a longitudinal study. Chest 126 (1), 59–65. https://doi.org/10.1378/chest.126.1.59.

Sturmberg, J.P., Bennett, J.M., Martin, C.M., Picard, M., 2017. 'Multimorbidity' as the manifestation of network disturbances. J. Eval. Clin. Pract. 23 (1), 199–208. https://doi.org/10.1111/jep.12587.

Sum, G., Hone, T., Atun, R., Millett, C., Suhrcke, M., Mahal, A., et al., 2018. Multimorbidity and out-of-pocket expenditure on medicines: a systematic review. BMJ Glob. Health 3 (1), e000505. https://doi.org/10.1136/bmjgh-2017-000505.

Taylor, T.L., Killaspy, H., Wright, C.A., Turton, P., White, S., Kallert, T.W., et al., 2009. A systematic review of the international published literature relating to quality of institutional care for people with longer term mental health problems. BMC Psychiatry 9, 55. https://doi.org/10.1186/1471-244X-9-55.

Teh, R.O., Menzies, O., Connolly, M.J., Doughty, R.N., Wilkinson, T.J., Pillai, A., et al., 2018. Patterns of multi-morbidity and prediction of hospitalisation and all-cause mortality in advanced age. Age Ageing 47 (2), 261–268. https://doi.org/10.1093/ageing/afx184.

Wang, H.H.X., Wang, J.J., Lawson, K.D., Wong, S.Y.S., Wong, M.C.-S., Li, F.J., et al., 2015. Relationships of multimorbidity and income with hospital admissions in 3 health care systems. Ann. Fam. Med. 13 (2), 164–167. https://doi.org/10.1370/afm.1757.

Wang, L.-D., Kong, L.-z., Wu, F., Bai, Y., Burton, R.C., 2005. Preventing chronic diseases in China. Lancet 366 (9499), 1821–1824. https://doi.org/10.1016/S0140-6736(05)67344-8.

Wang, X., Sun, X., Birch, S., Gong, F., Valentijn, P.P., Chen, L., et al., 2018. People-centred integrated care in urban China. Bull. World Health Organ. 96 (12), 843–852. https://doi.org/10.2471/BLT.18.214908.

Wang, X.Q., Chen, P.J., 2014. Population ageing challenges health care in China. Lancet 383 (9920), 870. https://doi.org/10.1016/S0140-6736(14)60443-8.

Wei, X., Li, H., Yang, N., Wong, S.Y.S., Chong, M., Shi, L., et al., 2015. Changes in the perceived quality of primary care in Shanghai and Shenzhen, China: a difference-in-difference analysis. Bull. World Health Organ. 93 (6), 407–416. https://doi.org/10.2471/BLT.14.139527.

West, S.G., Taylor, A.B., Wu, W., 2012. Model Fit and Model Selection in Structural Equation Modeling. Guilford Press, New York.

World Health Organization (WHO), 2008. The world health report 2008 – primary health care, now more than ever. WHO, Geneva, Switzerland. https://commed.vcu.edu/IntroPH/Primary_Care/2010/WHO08_overview_en.pdf. (Accessed 2 March 2023).

Yao, S., Cao, G., Han, L., Chen, Z., Huang, Z., Gong, P., et al., 2019. Prevalence and patterns of multimorbidity in a nationally representative sample of older Chinese: results from CHARLS. J. Gerontol. A Biol. Sci. Med. Sci. 75 (10), 1974–1980. https://doi.org/10.1093/gerona/glz185.

Yao, S., Cao, G., Han, L., Huang, Z., Chen, Z., Su, H.-X., et al., 2020. Associations between somatic multimorbidity patterns and depression in a longitudinal cohort of middle-aged and older chinese. J. Am. Med. Dir. Assoc. 21 (9), 1282–1287. https://doi.org/10.1016/j.jamda.2019.11.028.

Yao, S., Meng, X., Cao, G., Huang, Z., Chen, Z., Han, L., et al., 2020. Associations between multimorbidity and physical performance in older chinese adults. Int. J. Environ. Res. Public Health 17 (12), 4546. https://doi.org/10.3390/ijerph17124546.

Zhai, X., Zhang, Q., Li, X., Zhao, X., 2023. Association between multimorbidity patterns and catastrophic health expenditure among Chinese older adults living alone. Arch. Gerontol. Geriatr. 106, 104892 https://doi.org/10.1016/j.archger.2022.104892.

Zhang, R., Lu, Y., Shi, L., Zhang, S., Chang, F., 2019. Prevalence and patterns of multimorbidity among the elderly in China: a cross-sectional study using national survey data. BMJ Open 9 (8), e024268. https://doi.org/10.1136/bmjopen-2018-024268.

Zhao, Y., Atun, R.A., Oldenburg, B., McPake, B., Tang, S., Mercer, S.W., et al., 2020. Physical multimorbidity, health service use, and catastrophic health expenditure by socioeconomic groups in China: an analysis of population-based panel data. Lancet Glob. Health 8 (6), e840–e849. https://doi.org/10.1016/S2214-109X(20)30127-3.

Zhao, Y., Hu, Y.-s., Smith, J.P., Strauss, J., Yang, G., 2014. Cohort profile: the China health and retirement longitudinal study (CHARLS). Int. J. Epidemiol. 43 (1), 61–68. https://doi.org/10.1093/ije/dys203.

Zhao, Y., Zhang, P., Oldenburg, B., Hall, T., Lu, S., Haregu, T.N., et al., 2021. The impact of mental and physical multimorbidity on healthcare utilization and health spending in China: a nationwide longitudinal population-based study. Int. J. Geriatr. Psychiatry 36 (4), 500–510. https://doi.org/10.1002/gps.5445.