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The Reversibility of Central Obesity: Longitudinal Transitions and Determinants among Older Chinese Adults

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Abstract: Waist circumference (WC) is a key indicator of central obesity, yet longitudinal evidence regarding its state fluctuations in older Chinese populations is limited. This study utilized a nationally representative cohort of adults aged ≥45 years from the China Health and Retirement Longitudinal Study (CHARLS, 2011–2015) to investigate this dynamic process. By applying a continuous-time multi-state Markov model, we tracked bidirectional transitions among normal, borderline, and central obesity states. The analysis showed that WC status is highly reversible, with frequent shifts occurring mainly between normal and borderline levels. Furthermore, the determinants of these shifts are strongly state- and direction-specific. Female sex and multimorbidity were found to increase the risk of WC deterioration while reducing the likelihood of improvement. Additionally, lower education, instrumental activities of daily living (IADL) impairment, and depression showed asymmetric associations across the progression and regression pathways of central obesity. These findings underscore that WC changes are highly dynamic and asymmetric, emphasizing the importance of continuous monitoring and stage-tailored strategies for effective central obesity management in aging populations.

1. Introduction

While Body Mass Index (BMI) is the conventional metric for assessing obesity, it fails to differentiate between lean mass and adipose tissue or reflect regional fat distribution. WC, a direct indicator of visceral fat, has proven to be a superior and independent predictor of metabolic syndrome, atherosclerotic dyslipidemia, and cardiovascular disease[1]. Evidence shows that WC correlates more strongly with MRI-derived fat measurements than BMI and effectively identifies high-risk populations[2,3].

The health implications of WC are highly population- and age-specific. WC is an independent mortality risk factor even within a normal BMI range[4]. In older Chinese adults, longitudinal data indicate that an increasing WC—particularly when accompanied by weight loss—strongly predicts all-cause mortality[5]. Furthermore, the divergent effects of BMI and WC on mortality in the oldest-old (aged 80+) emphasize the need to prioritize WC in geriatric weight management[6].

Despite its clinical value, most existing research treats WC as a static exposure, neglecting how individuals transition between different WC categories over time. Using data from the China Health and Retirement Longitudinal Study (CHARLS), this study applies a Markov model to investigate the longitudinal transitions and determinants of WC states in middle-aged and older Chinese adults. By characterizing the dynamic trajectories of abdominal adiposity, this study provides empirical evidence to refine targeted prevention strategies for central obesity and chronic disease management.

2. Materials and Methods

2.1. Data Source and Study Population

This study used data from three waves (2011, 2013, and 2015) of the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative cohort[7]. From the initial 2011 baseline, we excluded participants who were aged <45 years, had fewer than two WC measurements across the waves, reported implausible WC values (<50 or ≥150 cm), or lacked >30% of covariate data. The final analytic sample comprised 7,014 individuals (Figure 1).

2.2. Definition and Assessments of the WC

WC was measured horizontally at the navel level at the end of a normal exhalation[8]. Based on sex-specific cutoffs[9] , participants were classified into three states: normal (<85 cm for men, <80 cm for women), borderline central obesity (85–89.9 cm for men, 80–84.9 cm for women), and central obesity (≥90 cm for men, ≥85 cm for women).

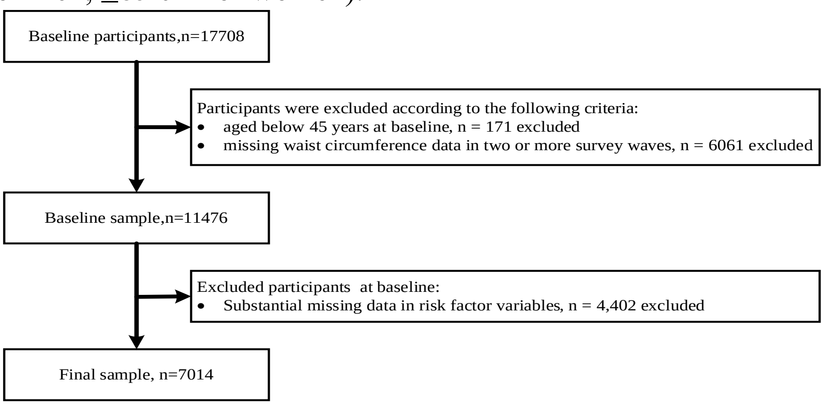

Figure 1 Study sample screening flowchart.

2.3. Measurement of Covariates

Baseline covariates included sociodemographic factors, lifestyle behaviors, and health status. Missing covariate data were imputed using multiple imputation by chained equations, and outliers were handled via the median absolute deviation approach(Table 1).

Table 1 Baseline characteristics by WC category among middle-aged and older adults.

Group	Variable	Category	Normal(%)	Borderline(%)	Central(%)
Sociodemographic characteristics	age	45-59	38.5	45.5	43.1
		60-74	50.2	45.4	49.1
		≥75	11.3	9.2	7.8
	gender	Man	54.7	39.3	28.1
		Woman	45.3	60.7	71.9

	education	> Elementary	22.7	25.9	27.5
		≤Elementary	77.3	74.1	72.5
	marital status	Married	86.8	88.1	88.6
		Unmarried	13.2	11.9	11.4
	residence	Rural	89.4	83.0	79.2
		Urban	10.6	17.0	20.8
Health status	IADL	Intact	75.6	77.6	76.5
		Impaired	24.4	22.4	23.5
	depression	Depressed	54.0	48.3	45.7
		Non-depressed	46.0	51.7	54.3
	multimorbidity	YES	39.9	41.3	49.9
		NO	60.1	58.7	50.1
Lifestyle factors	life satisfaction	Dissatisfied	20.7	16.9	16.1
		Satisfied	79.3	83.1	83.9
	physical activity difficulty	YES	84.0	83.8	87.0
		NO	16.0	16.2	13.0
	sleep	Abnormal	49.2	46.8	46.8
		Normal	50.8	53.2	53.2
	smoking	Smoker	39.9	24.6	17.3
		Non-smoker	60.1	75.4	82.7

2.4. Multi-State Model with Feature Selection

Data cleaning and preliminary analyses were conducted in Stata 17, and statistical modeling was performed in R 4.5.2. Based on empirical observations of frequent, bidirectional individual-level progression and regression across the three WC states despite a stable population-level distribution (Figure 2,Table 2), we specified a fully connected, continuous-time homogeneous multi-state Markov model [14, 15] to capture these dynamic transitions (Figure 3). To minimize overfitting, candidate covariates were initially screened using multinomial logistic regression with a Least Absolute Shrinkage and Selection Operator (LASSO) penalty, optimized via five-fold cross-validation (one-standard-error rule). The variables consistently retained by LASSO were subsequently incorporated into the Markov model to estimate transition-specific hazard ratios (HRs) via maximum likelihood using the msm package. All analyses were executed across 10 multiply imputed datasets to account for missing values, with final parameter estimates and standard errors pooled according to Rubin's rules.

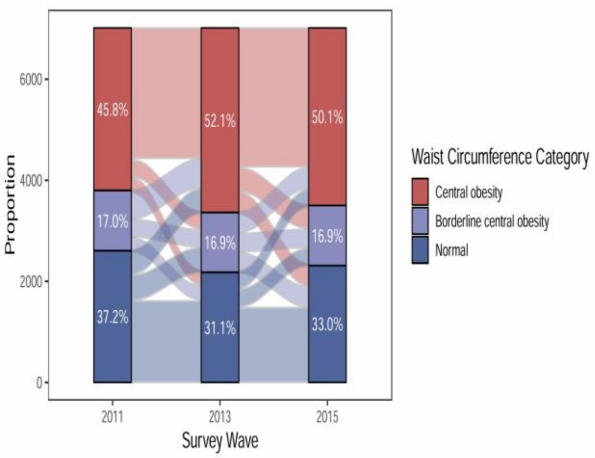

Figure 2 WC Status: Composition and transitions.

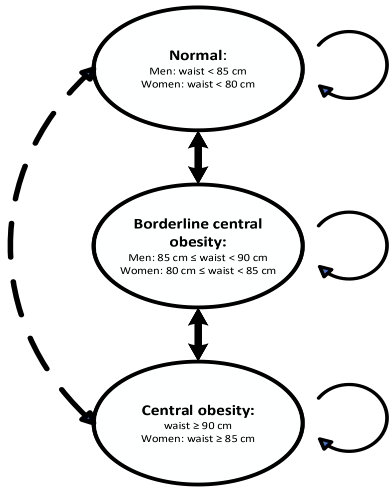

Figure 3 Hypothesized Markov transition diagram for WC status change.

Table 2 Transition frequencies and intensities.

Transition	To: Normal			To: Borderline			To: Central		
From	Freq.	Inten.	95%CI	Freq.	Inten.	95%CI	Freq.	Inten.	95%CI
Normal	3105.2	-0.278	[-0.295,-0.260]	674.4	0.337	[0.295,0.379]	718.8	0.048	[0.039,0.056]
Borderline	834.6	0.21	[0.188,0.233]	694.5	-0.787	[-0.852,-0.722]	824.1	0.125	[0.111,0.139]
Central	874.4	0.067	[0.052,0.083]	992.2	0.45	[0.407,0.492]	5309.8	-0.173	[-0.184,-0.161]

Note: Freq. = Frequency, Inten. = Intensity.

3. Results

3.1. Baseline characteristics of study participants

A total of 7,014 middle-aged and older adults were included. The majority were aged 60–74 years, married, rural residents, with an educational level of elementary school or below. Notably, the proportion of women increased markedly with worsening WC status, rising from 45.3% in the normal group to 71.9% in the central obesity group. Central obesity was also positively associated with urban residence and multimorbidity. Paradoxically, the prevalence of smoking declined as WC categories worsened, while sleep abnormalities and physical activity difficulties were common across all groups (Table 1).

3.2. Longitudinal transitions of WC status

While the population-level WC distribution appeared stable across the three waves, individual-level transitions were highly dynamic (Table 2). Based on the estimated transition intensity matrix, shifts occurred predominantly between adjacent states. For instance, individuals with normal WC were far more likely to progress to borderline central obesity than to leap directly to central obesity. Similarly, regression from central obesity usually halted at the borderline state rather than reaching full recovery. Markov model projections (Figure 4)highlighted this chronicity: the probability of maintaining a normal WC declined from 0.65 at year 2 to 0.40 at year 6, while those starting with central obesity generally persisted in abnormal states, experiencing only partial regression over extended follow-ups.

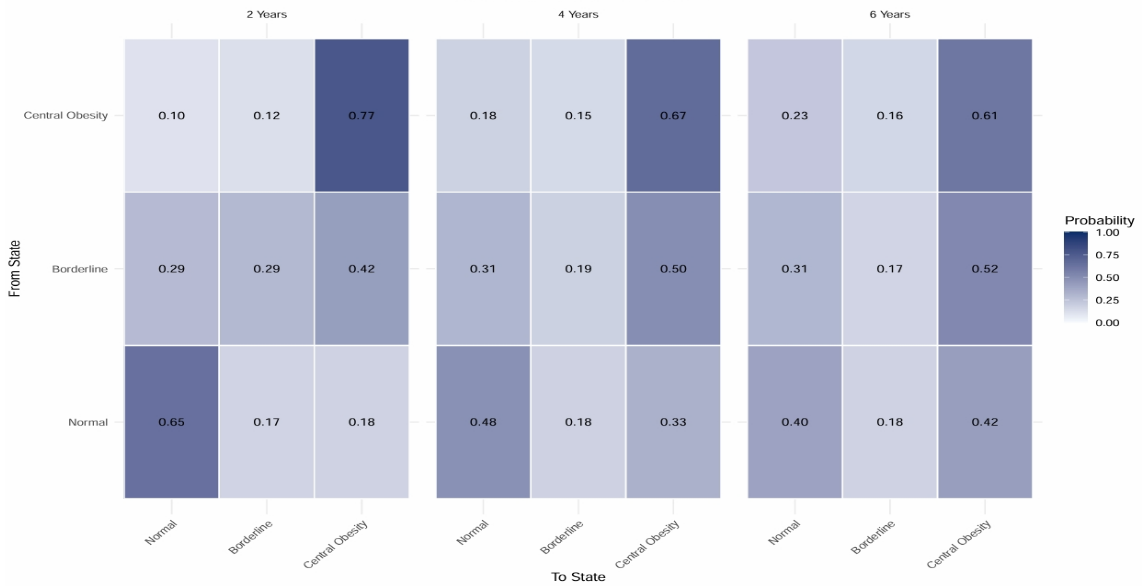

Figure 4 WC State Transition Probability Heatmap (Multistate Markov Model Predictions).

3.3. Estimated hazard ratios for the effects of each variable on WC transition intensities

Using the LASSO method, we identified 11 key variables influencing WC transitions. The multistate Markov model results (Table 3) revealed that gender and multimorbidity were the most profound drivers. Compared to men, women faced an 85% higher risk of progressing from normal to borderline WC (HR = 1.85, 95% CI: 1.35–2.52) and a 51% lower likelihood of fully recovering from central obesity (HR = 0.49). Conversely, the absence of multimorbidity not only protected against early fat accumulation (HR = 0.79) and further progression (HR = 0.75), but also more than doubled the chances of full recovery to normal WC (HR = 2.06).

Interestingly, several counterintuitive associations emerged. Lower educational attainment and IADL impairment significantly protected against the initial transition from normal to borderline WC (HR = 0.71 and 0.75, respectively). Furthermore, non-depressed individuals were less likely to recover from central obesity than depressed participants (HR = 0.62), and non-smokers showed a higher risk of progressing to central obesity compared to smokers (HR = 1.38).

Table 3 Estimated hazard ratios of exposure factors on WC state transition intensities (multi-state model).

Variable	Category	S1→S2	S1→S3	S2→S1	S2→S3	S3→S1	S3→S2
age	45–59	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	60–74	1.11(0.83,1.48)	0.76(0.39,1.47)	1.11(0.79,1.57)	1.08(0.86,1.36)	0.95(0.56,1.60)	1.10(0.84,1.44)
	≥75	1.07(0.64,1.78)	0.69(0.04,10.67)	1.49(0.92,2.43)	0.83(0.50,1.38)	0.94(0.31,2.87)	1.09(0.70,1.69)
gender	Man	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	Woman	1.85(1.35,2.52)***	1.85(0.84,4.08)	1.23(0.88,1.73)	1.17(0.90,1.53)	0.49(0.31,0.78)**	0.88(0.66,1.16)
education	>Elementary	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	≤Elementary	0.71(0.52,0.97)*	0.87(0.44,1.73)	0.88(0.65,1.20)	1.01(0.77,1.33)	1.05(0.69,1.59)	1.22(0.93,1.61)
residence	Rural	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	Urban	0.84(0.58,1.22)	1.97(0.98,3.99)†	0.81(0.55,1.19)	0.96(0.71,1.28)	0.77(0.41,1.44)	0.92(0.67,1.25)
IADL	Intact	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	Impaired	0.75(0.56,1.00)*	1.35(0.68,2.69)	0.95(0.70,1.28)	0.86(0.68,1.10)	1.29(0.83,2.00)	0.94(0.72,1.22)
depression	Depressed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	Non-depressed	1.08(0.85,1.36)	1.12(0.67,1.89)	1.05(0.80,1.37)	1.12(0.90,1.38)	0.62(0.39,0.99)*	1.08(0.84,1.39)
multimorbidity	YES	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	NO	0.79(0.63,0.99)*	1.33(0.68,2.58)	0.81(0.62,1.06)	0.75(0.60,0.94)*	2.06(1.30,3.24)**	1.01(0.78,1.31)
life satisfaction	Dissatisfied	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	Satisfied	1.30(0.96,1.77)†	0.83(0.47,1.47)	1.21(0.88,1.68)	1.10(0.83,1.46)	0.76(0.49,1.19)	1.03(0.74,1.43)
physical activity difficulty	YES	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	NO	1.00(0.73,1.36)	0.94(0.44,2.01)	0.94(0.65,1.35)	1.16(0.87,1.54)	1.06(0.55,2.05)	1.22(0.87,1.72)
sleep	Abnormal	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	Normal	0.84(0.68,1.03)†	1.22(0.80,1.87)	0.95(0.75,1.20)	1.01(0.85,1.21)	1.13(0.78,1.65)	0.87(0.70,1.09)
smoking	Smoker	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	Non-smoker	1.29(0.98,1.70)†	0.93(0.51,1.70)	0.95(0.67,1.34)	1.38(1.02,1.87)*	0.69(0.44,1.07)†	1.04(0.72,1.52)

Notes: Data are presented as Hazard Ratio (95% CI). S1: Normal; S2: Borderline central obesity; S3: Central obesity. Ref. denotes the reference category.
Significance levels: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4. Discussion

Using a continuous-time multi-state Markov model, this study reveals that WC transitions in older Chinese adults are highly dynamic and asymmetric. Transition trajectories are profoundly shaped by gender and systemic health. Women exhibit a higher susceptibility to central obesity and a lower likelihood of reversal, largely driven by postmenopausal estrogen declines[10,11]and socioenvironmental barriers to physical activity[12].Conversely, the absence of multimorbidity provides robust bidirectional protection, whereas chronic conditions exacerbate visceral adiposity through inflammation and metabolic dysregulation[13,14].

Interestingly, several factors typically associated with vulnerability actually restricted abdominal fat accumulation. Lower education and impaired IADL protected against early WC progression, likely reflecting lifelong manual labor in rural settings[15]and involuntary caloric restriction due to functional decline[16,17].Similarly, the apparent WC "recovery" observed among smokers[15]and depressed individuals indicates pathological weight loss—such as nicotine-induced appetite suppression or late-life anorexia—rather than proactive health improvement[18,19].

5. Conclusion

While integrating LASSO selection with the Markov framework effectively captures these complex dynamics, our study is limited by the model's memoryless assumption, unmeasured confounders, and the reliance on WC as a proxy rather than direct adiposity imaging. Nevertheless, our findings emphasize that central obesity in aging populations requires continuous, state-specific monitoring and targeted interventions, particularly focusing on women and individuals with multimorbidities.

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