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Dynamic cross-lagged effects between healthy lifestyles and multimorbidity among middle-aged and older adults in China

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Abstract

Background While healthy lifestyles mitigate the risk of multimorbidity (≥ 2 chronic diseases), their temporal dynamics in aging populations, particularly in low- and middle-income countries undergoing rapid demographic structure transition, remain understudied.

Methods Using longitudinal data (2014–2020) from 6,852 Chinese adults (aged ≥ 45 years) in the China Family Panel Studies, we used the subgroup analysis to investigate high risk groups in the chronic diseases status, employed alluvial diagrams to visualize diseases status transition and random intercept cross-lagged panel model to quantify the lagged effect between healthy lifestyles (sleep, physical exercise, smoking, drinking) and chronic diseases status (without diseases, single, multimorbidity).

Results Compared to male, urban and middle-aged individuals, female, rural and older adults demonstrated more severe chronic diseases status ($P < 0.05$). The proportion of people with multimorbidity increased over time, from 9.2% in 2014 to 29.1% in 2020. A total of 37.8% of participants experienced diseases status transition, and more than half of whom progressed to multimorbidity. Disease trajectories disproportionately progressed toward multimorbidity. The direction and size of the cross-lagged effects are dynamic. Healthier lifestyles predicted reduced disease severity from 2014 to 2018 (β_1=-0.106, $P_1 < 0.001$; β_2=-0.111, $P_2 < 0.001$), but this protective effect reversed post-2018, with multimorbidity predicting lower probability of choosing healthy lifestyles (β_3=-0.160, $P_3 < 0.001$).

Conclusions Our study demonstrates dynamic cross-lagged effect exists between healthy lifestyles and chronic diseases status in middle-aged and older Chinese. Disease trajectories and lifestyle-disease interplay reveal critical time-sensitive windows for intervention. Early-stage lifestyle promotion could delay progression, whereas later-stage disease management requires system-level strategies addressing urban-rural healthcare disparities and self-efficacy barriers. These findings directly inform China's Healthy Aging 2030 priorities.

Keywords Healthy lifestyles, Multimorbidity, Dynamic cross-lagged effects, Proactive health, Healthy aging

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Background

Chronic diseases, characterized by insidious onset, a prolonged course, and complex interactions, remain the main cause of global morbidity and mortality and pose a significant threat to public health worldwide [1–3]. In China, the prevalence of chronic diseases and multimorbidity (≥ 2 chronic diseases) among middle-aged and older people (aged ≥ 45 years) are 44.4% and 30.4%, respectively [4]. These conditions disproportionately affect middle-aged and older adults, who are particularly susceptible to developing multimorbidity. Multimorbidity often leads to functional decline, decreased quality of life, and increased healthcare utilization and costs [5–7]. Moreover, China's rapid aging population (projected to exceed 30% aged ≥ 60 by 2035) [8] and pronounced urban-rural healthcare disparities exacerbate vulnerability to multimorbidity, underscoring the urgency of region-specific interventions [9]. Therefore, initiatives such as the "Healthy China Action Plan 2019–2030" and the "Healthy China 2030 Initiative" emphasize the proactive health concept of "individuals have the primary responsibility for their own health" to advocate choosing healthy lifestyles, improving the effectiveness of chronic diseases health management, and achieving the United Nations Sustainable Development Goals and the Healthy China 2030 objectives [10]. The proactive adoption of healthy lifestyles, including moderate physical exercise, smoking cessation, alcohol restriction, adequate sleep, and balanced nutrition, has been shown to delay the onset and progression of chronic diseases effectively [5, 11–13]. Furthermore, studies highlight the synergistic benefits of adhering to multiple healthy lifestyles. Greater adherence to healthy lifestyles is associated with reduced chronic diseases incidence and extended life expectancy [14].

Motivated by global health priorities and the escalating burden of chronic diseases, extant literature has made substantial contributions to understanding lifestyle-disease associations among middle-aged and older adults [15–17]. However, some critical gaps should be addressed. First, prior studies have inadequately addressed the longitudinal trajectories of diseases status transition, most of which have focused on systematic classification and influencing factors of chronic diseases or multimorbidity patterns [7]. Second, cross-sectional designs and conventional models limit causal inferences regarding the longitudinal evolution relationship [12]. Although recent studies highlight the need for dynamic modeling to capture disease progression, relevant research is still rare [18]. Third, many studies pay more attention to the one-way or static correlation between healthy lifestyles and chronic diseases, while the research on the combination of dynamic trajectories and cross-lagged effects is still lacking [15, 19, 20]. Finally, existing evidence predominantly originates from high-income Western countries [21–23]with limited representation from low- and middle-income countries (LMICs) such as China [24–26].

To address these gaps, we used four-phase longitudinal survey data from the China Family Panel Studies (CFPS) from 2014 to 2020. First, we utilized alluvial plots to visualize the dynamic transition of chronic diseases status across waves. Second, we implemented the random intercept cross-lagged panel model (RI-CLPM) to disentangle between-person heterogeneity from within-person temporal dynamics, estimate cross-lagged effects (healthy lifestyles→future chronic diseases status, and vice versa), and reduce estimation biases stemming from unmeasured confounders. Meanwhile, the model disentangles bidirectional dynamic pathways—such as "healthy lifestyles →chronic diseases status" and "chronic diseases status→ healthy lifestyles" —thereby enabling a more flexible analysis of the dynamic, reciprocal relationship between healthy lifestyles and chronic diseases status. Our findings not only offer evidence for the onset and progression of chronic diseases but also highlight the significance of understanding disease status transition and the evolutionary relationship between healthy lifestyles and disease status. Additionally, we further underscore the unique contributions of this research in China and discuss how to promote the concept of "proactive health" to effectively address the challenges of population aging effectively.

Methods

Study population

We analyzed data from the CFPS four-phase tracking dataset (2014–2020). Individuals who were lost to follow-up, aged < 45 years, and lacking demographic information, lifestyle behavior, and chronic diseases status were excluded (see supplementary material Figure S1). Ultimately, 6,852 middle-aged and older Chinese were included in the study, and all the data formed panel data. The demographic information was determined by self-reported in 2014. Healthy lifestyles and chronic diseases status were used for repeated measurements and updated on a biennial basis.

Key measures

The dependent variable was the individual's chronic diseases status (CDs). In accordance with the definitions of chronic diseases set forth by the World Health Organization (WHO) and China's Medium and Long-term Plan for the Prevention and Treatment of Chronic Diseases (2017–2025), this study selected eight priority chronic diseases, namely, diabetes, cerebrovascular disease, chronic obstructive disease, hypertension, cancer, chronic nephritis and nephropathy, and depression

[27, 28]. According to the number of chronic diseases, the subjects included in the analysis were classified into three subgroups: multimorbidity (≥ 2 chronic diseases mentioned above), only one chronic disease, and without chronic diseases. 3 point represents multimorbidity, 2 points indicate only one chronic disease, and 1 points represent without chronic diseases.

The independent variable was healthy lifestyles (HL), which included four key lifestyles: sleep time, weekly physical exercise frequency, smoking, and drinking. These domains are used to comprehensively evaluate the healthy behavior status of middle-aged and older adults [29, 30]. On the one hand, research has shown that sleep onset after 23:00 has a detrimental effect on the health of the heart and other vital organs in middle-aged and older people [31]. On the other hand, due to objective reasons, CFPS lacks other indicators to evaluate sleep time (such as duration of overall sleep or nap), so the sleep score was simplified as follows: sleep onset after 23:00 (0 point), before and 23:00 (1 point).

According to the WHO "Guideline on Physical Activity and Sedentary Behavior", which recommends that adults (≥ 18 years old) perform 150 min (≥ 5 times a week, ≥ 30 min each time) of moderate-intensity aerobic activity per week to reduce the risk of chronic diseases [32]. The threshold is consistent with China's health guidelines (e.g., the national fitness guidelines, the hypertension/diabetes chronic disease exercise guidelines, and weight management guidelines) [33–35]. Thus, the options for weekly average physical exercise frequency (see supplementary material Table S1) were classified to three groups: never or rarely a week, 1–4 times a week, and 5 times a week and above. After that, we standardized the scores (range:0–1) to ensure that the four key domains had the same weight in healthy lifestyles. Smoking and drinking were assigned with 0 representing yes, and 1 representing no. The total HL score (range:0–4) was derived by summing standardized scores for sleep (range:0–1), the physical exercise score (range:0–1), the smoking score (range:0–1), and the drinking score (range:0–1).

Covariates

Combined with previous research results, gender, age, marital status, urban/rural, education level, and occupation type have an impact on the independent variables and dependent variables determined in our study [14, 23, 29, 36]. Therefore, we selected the covariates as gender, age, marital status, urban/rural, education level, and occupation type. The coding of all variables can be seen in the supplementary material Table S2. At the same time, given that the impact of these variables on the evolution of multimorbidity is a long dynamic process [36] we used the data from the 2014 baseline survey.

The RI-CLPM

The specific RI-CLPM is illustrated in Fig. 1, which does not present the path of each covariates [37]. W1 ~ W4 represent the four phases of 2014–2020, with an interval of 2 years. The HL-W1 ~ HL-W4 and CDs-W1 ~ CDs-W4 variables represented the measurement values of healthy lifestyles scores and chronic diseases status scores, respectively. The HL between-person and CDs between-person variables represent the trait bias of healthy lifestyles and chronic diseases status among the subjects, respectively. The HL within-person and

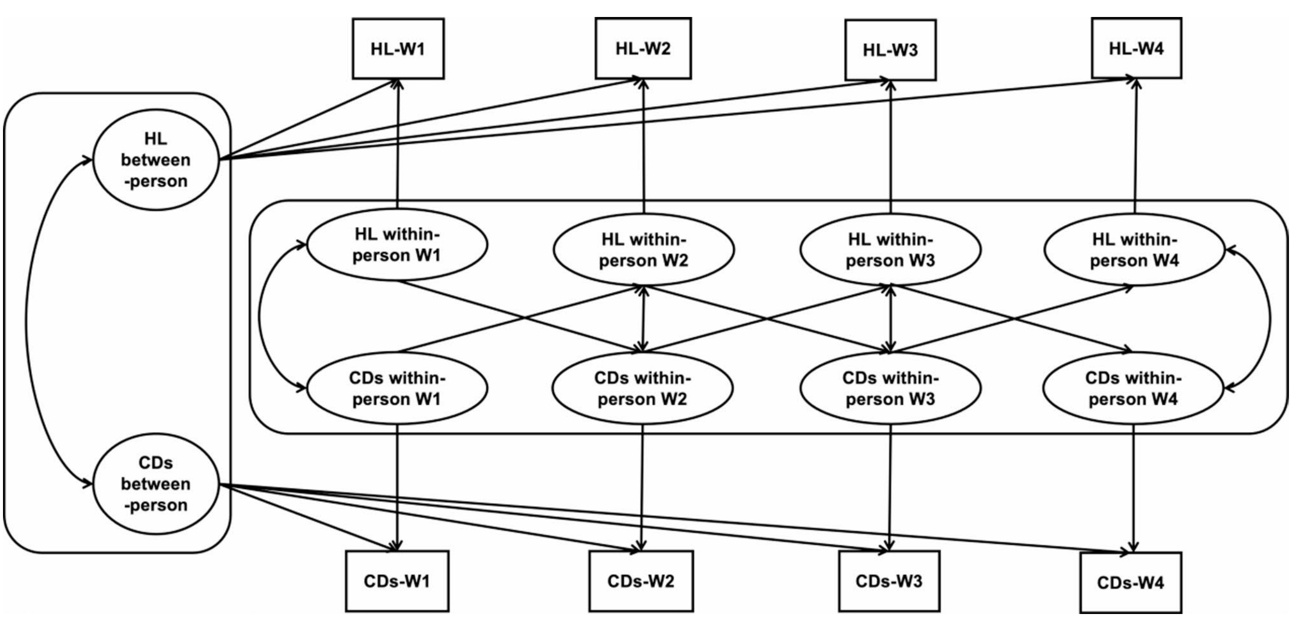

Fig. 1 The random intercept cross-lagged panel model of healthy lifestyles and chronic diseases status

CDs within-person variables represented the distance between the expected value and the healthy lifestyle and chronic diseases status at each time point. The expression of the RI-CLPM is as follows:

$$HL_{iw} = \mu_w + \omega_i + p_{iw} \tag{1}$$

$$CDs_{iw} = \pi_w + \theta_i + q_{iw} \tag{2}$$

$$p_{iw} = \alpha_w p_{i,w-1} + \beta_w q_{i,w-1} + u_{iw} \tag{3}$$

$$q_{iw} = \delta_w q_{i,w-1} + \gamma_w p_{i,w-1} + v_{iw} \tag{4}$$

In formula (1) and (2), $\mathrm{HL_{iw}}$and $\mathrm{CDs_{iw}}$ represent the measured values of HL and CDs for individual i at period w, respectively. α_w and π_w represent the mean values of HL and CDs at period w. ω_i and θ_i are the trait bias latent variables of individual i from the mean values of HL and CDs, the magnitude of which does not vary over time. $\mathrm{p_{iw}}$ and $\mathrm{q_{iw}}$ are the deviations of HL and CDs for individual i from their expected values $\mu_w + \omega_i$ and $\pi_\mathrm{w}{+}\theta_\mathrm{i}$ at period w, representing the intra-individual deviations of HL and CDs at each time point.

In formula (3) and (4), α_w and δ_w are the autoregressive path coefficients of individual i at period w. These coefficients indicate the degree to which the variable value at period w-1 influences the variable value at period w. Additionally, they elucidate the practical significance of lagged transition in the effect. β_w and γ_w represent the cross-lagged path coefficients between the variables HL and CDs of individual i at period w, which are used to identify correlation and direction. γ_w represents the influence of HL at w-1 on CDs at w, after controlling for the autoregressive effect of CDs at w-1. The same logic applies to β_w. Finally, based on the Stable Unit Treatment Value Assumption, we test whether β_w and γ_w are statistically significant and compare them to explore the timing relationship and strength between variables HL and CDs. $\mathrm{u_{iw}}$ and $\mathrm{v_{iw}}$ are residuals.

Sensitivity analyses

The COVID-19 pandemic in 2020 changed the lifestyles of the population and disrupted the order of medical services. We conducted sensitivity analyses to assess potential confounding during the final wave of data collection (2020) [38–43]. First, we reran the RI-CLPM model only using data from 2014 to 2018 to examine whether the lagged effects persisted. Second, we introduced an additional covariate in the full model to capture pandemic-specific impacts: the lockdown index, which indicates the severity of the lockdown in the area where the participants live (from the Oxford COVID-19 Government Response Tracker, OxCGRT) [44]. We select the StringencyIndex of China in 2020 from the OxCGRT, and calculate the mean by fitting the StringencyIndex curve. The mean was used as the value of the lockdown index in each province. Model fit indices, such as the comparative fit index (CFI), Tucker-Lewis index (TLI) and root mean square error of approximation (RMSEA), were compared to evaluate robustness.

Using a four-phase follow-up sample may introduce non-random missing data. To address this, we applied inverse probability weighting (IPW) to re-weight baseline data and mitigate survivorship bias caused by attrition due to mortality and other reasons. Firstly, we estimated individual attrition probabilities using a logistic regression model, with covariates, health lifestyles, and number of chronic diseases. Secondly, the IPW weights were incorporated into analysis to reassess associations between health lifestyles and chronic diseases status.

Statistical analysis

Analyses were conducted using Stata 17.0 (Stata Corp., College Station, TX, USA), SPSS 25.0 (SPSS Inc., Chicago, IL, USA), Origin 2024 (OriginLab Corp., Northampton, MA, USA) and Mplus 8.3 (Muth´en & Muth´en, 1998–2017). The first step involved screening, cleaning the data of CFPS from 2014 to 2020, and encoding the variables. In the second step, we calculated the mean and standard deviation of the variables, examined the chronic diseases status subgroup analysis by covariates, used the Herman single-factor test to analyze the common method bias (the systematic errors caused by using a single data source or measurement method), and used the Spearman correlation test to analyze the correlation between healthy lifestyles scores and chronic diseases status scores. In the third step, we utilized an alluvial plot to demonstrate the trajectory of diseases status transition and RI-CLPM to explore the dynamic lagged effect between healthy lifestyles and chronic diseases status of middle-aged and older adults. Finally, we conducted sensitivity analyses to assess potential confounding from the COVID-19 pandemic during the final wave of data (2020) and using IPW to reduce the survivors bias. The level of significance was set at $\alpha = 0.05$.

Results

Baseline characteristics

A total of 6,852 participants were included in the study. Baseline characteristics from 2014 survey indicated that 82.4% of participants reported sleeping before 23:00 (including 23:00), and 34.2% engaged in regular physical exercise per week. The prevalence of non-smokers and non-drinkers in the past month was 68.3% and 81.8%, respectively. Among participants, 76.2% had no chronic diseases, 14.6% had one chronic disease, and 9.2% had multimorbidity. Demographically, 64.7% were aged 45–59 years old, 50.0% were female, 91.6% were married, and 55.6% resided in rural areas. Additionally, 34.0% were illiterate/semi-illiterate, and 37.9% were farmers (Table 1).

We also examined the chronic diseases status between 2014 and 2020 in subgroups analysis by gender, age, marital status, urban/rural, education level and occupation type. The results showed that there were differences in gender, urban/rural and age (all $P<0.05$). Compared to male, urban and middle-aged individuals, female, rural and older adults demonstrated more severe chronic diseases status.

Common method bias

The Herman single-factor test revealed that the total number of factors with eigenvalues greater than 1 in the four phases (2014–2020) was 2, and the variation explained by the largest factor were 38.3%, which was less than the critical standard of 50% [45, 46]. It indicated no clear common method deviation in the four phases of measurement and can construct a RI-CLPM for analysis.

Descriptive statistics and correlations

Descriptive statistics were conducted to assess sample characteristics and preliminary relationships between variables. The dependent variable has a skewed distribution, so we used the Spearman correlation test to analyze the correlations among variables. Means, standard deviations, and correlations for variables (i.e., healthy lifestyles and chronic diseases status) at each phase were estimated and are represented in Table 2. Spearman correlation analysis indicated consistent negative associations between healthy lifestyles and chronic diseases status

Table 1 Baseline characteristics of participants in 2014 ($n=6,852$)

Variable	Type	Frequency(n)	Percent(%)
Independent Variable			
Sleep time	After 23:00	1,209	17.6
	23:00 and before	5,643	82.4
Physical exercise frequency	never or rarely	4,506	65.8
	1–4 times a week	524	7.6
	5 times a week or more	1,822	26.6
Smoking last month	Yes	2,174	31.7
	No	4,678	68.3
Drinking last month	Yes	1,247	18.2
	No	5,605	81.8
Dependent Variable			
Chronic diseases status	multimorbidity	631	9.2
	only one chronic disease	1,001	14.6
	without chronic diseases	5,220	76.2
Covariates			
Gender	male	3,428	50.0
	female	3,424	50.0
Age(years)	45~59	4,434	64.7
	60~74	2,303	33.6
	≥ 75	115	1.7
Marital Status	married	6,281	91.7
	not married	571	8.3
Urban/Rural	rural	3,810	55.6
	urban	3,042	44.4
Education level	illiterate/semi-illiterate	2,331	34.0
	primary school	1,541	22.5
	junior high school	1,830	26.7
	high school/technical school/vocational high school	899	13.1
	junior college/undergraduate and above	251	3.7
Occupation type	farmers	2,595	37.9
	employees of enterprise and institutions	473	6.9
	employees of enterprises or flexible employees	1,110	16.2
	retirees	1,819	26.5
	unemployed	782	11.4
	social work professionals	52	0.7
	other unknown professionals	21	0.3

Table 2 Descriptive statistics and correlations between healthy lifestyles scores and chronic diseases status scores

	HL-W1	HL-W2	HL-W3	HL-W4	CDs-W1	CDs-W2	CDs-W3	CDs-W4
HL-W1[a]	1.000							
HL-W2	0.651**	1.000						
HL-W3	0.616**	0.653**	1.000					
HL-W4	0.602**	0.392**	0.634**	1.000				
CDs-W1[b]	-0.110**	-0.114**	-0.102**	-0.093**	1.000			
CDs-W2	-0.080**	-0.110**	-0.108**	-0.071**	0.289**	1.000		
CDs-W3	-0.067**	-0.118**	-0.131**	-0.091**	0.255**	0.307**	1.000	
CDs-W4	-0.072**	-0.072**	-0.092**	-0.071**	0.222**	0.280**	0.324**	1.000
M(SD)[c]	2.85(0.86)	2.93(0.85)	2.98(0.84)	3.37(0.77)	1.32(0.64)	1.35(0.67)	1.38(0.70)	1.52(0.88)

Note: [a]HL-W1: Healthy lifestyles scores at Wave 1 (2014), higher scores indicated healthier lifestyles, other similarly

[b]CDs-W1: Chronic diseases status scores at Wave 1 (2014), higher scores indicated severe disease status (greater chronic disease burden), other similarly

[c]Mean and standard deviation of healthy lifestyles scores and chronic diseases status scores in each period

** represents a *P*-value < 0.01

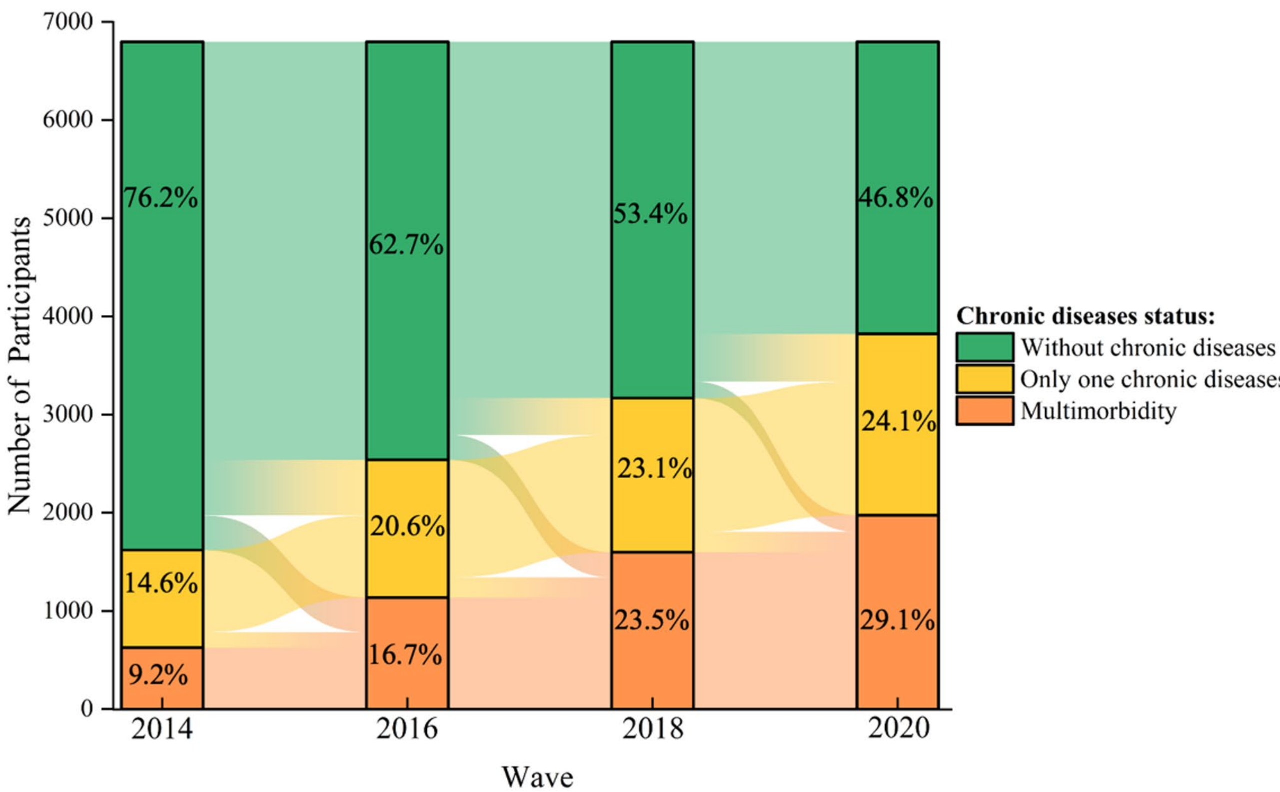

Fig. 2 Alluvial plot of the chronic diseases status transition among the middle-aged and older Chinese from 2014–2020 (the shadow part shows the flow of disease status in each wave)

across all waves (all $P < 0.01$), and higher HL scores were correlated with milder chronic diseases status (fewer chronic diseases), indicating high stability between the variables and aligning with the prerequisites for cross-lagged analysis.

Chronic diseases status transition

Figure 2 illustrates the disease status transition between disease status (without chronic diseases, only one chronic disease, multimorbidity) across the four waves, and the lengths of the alluvial plot correspond to the percentage and number of participants. From 2014 to 2020, the proportion of middle-aged and older Chinese without chronic diseases declined from 76.2 to 46.8%, while those with only one chronic disease and multimorbidity increased from 14.6 to 24.1% and from 9.2 to 29.1%, respectively (see supplementary material Table S3). A total of 2589 (37.8% of the cohort) experienced a change of chronic diseases status. Among participants whose diseases status changed, 1,228 changed from without chronic diseases to only one chronic disease, and 1,361 changed from only one chronic disease to

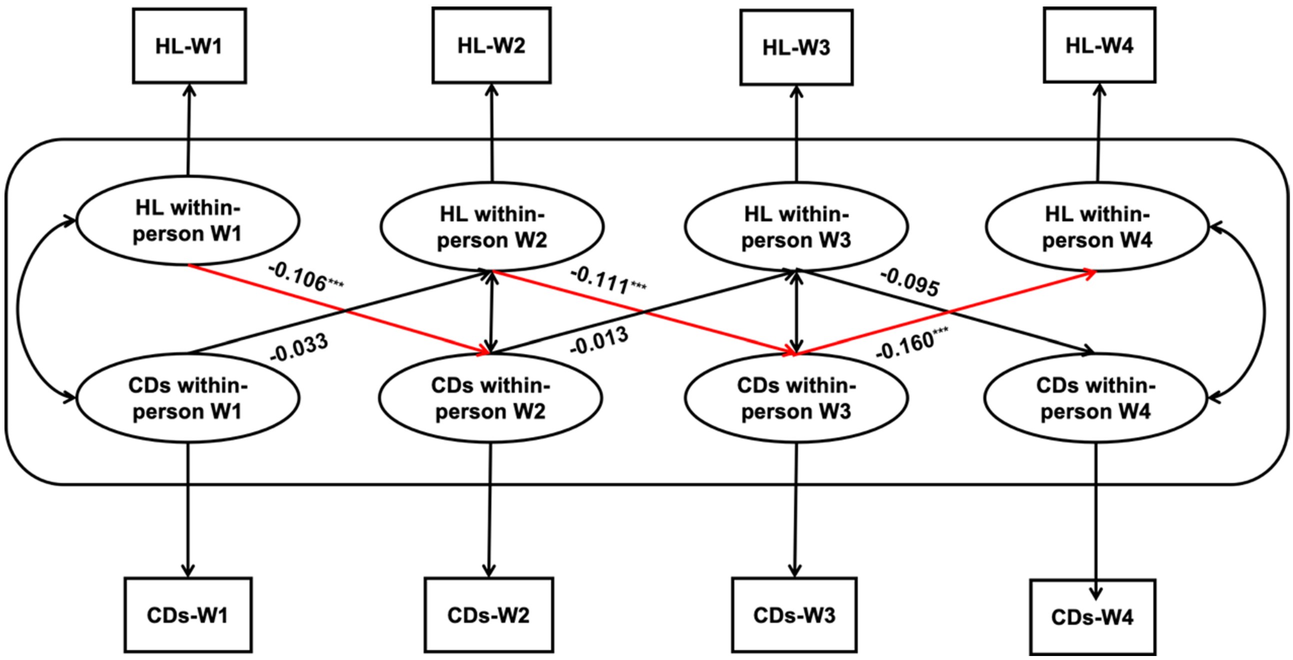

Fig. 3 The standardized coefficients of the cross-lagged effect and path simplification diagram of healthy lifestyles and chronic diseases status (the number on the arrow were the cross-lagged effect coefficients, and the red line indicates that the path was significant)

multimorbidity, exceeding transition to single-disease status. Aging and the presence or severity of chronic diseases were associated with a higher probability of transitioning to multimorbidity. Specifically, in cases where an individual is afflicted with a chronic disease or has severe disease status, the complex biological interaction between aging and diseases is likely to become more pronounced over time, thereby inducing the onset of other chronic diseases and increasing the risk of multimorbidity.

Cross-lagged effect

We constructed a RI-CLPM to investigate the associations between healthy lifestyles scores and chronic diseases status scores from 2014 to 2020 (W1-W4) and demonstrated acceptable fit (CFI = 0.930, TLI = 0.968, RMSEA = 0.04). Figure 3 demonstrates the path standardized coefficients and the RI-CLPM simplification diagram. Significant cross-lagged effects from healthy lifestyles to chronic diseases status were observed in the W1→W2 and W2→W3 period (β_1=-0.106, $P_1 < 0.001$; β_2=-0.111, $P_2 < 0.001$), which means that individuals with healthier lifestyles (relative to an individual's own mean) were likely to experience less chronic disease burden in the first three waves (see supplementary material Table S4). These findings indicate that healthy lifestyles in the present period, have a positive effect on diseases status in the next period, such as reducing the occurrence and deterioration of chronic diseases, and temporarily delaying the transition of diseases status. Conversely, a reverse effect emerged in the W3→W4 period (β_3=-0.160, $P_3 < 0.001$), which means that individuals with more severe disease status were less likely to choose healthy lifestyles in the fourth wave. It indicated that the risk of transforming multimorbidity and the exacerbation of chronic diseases gradually increase over time, and the positive impact of healthy lifestyles is counterbalanced by the negative effect of severe disease status. Middle-aged and older adults with current multimorbidity or severe diseases status were less likely to maintain healthy lifestyles, thus they had lower healthy lifestyles scores in the subsequent period. It also showed that the impact between healthy lifestyles and chronic diseases varies in intensity over time, and the protective effect of healthy lifestyles on health outcomes is more effective in the early stages, while chronic diseases weaken the ability of people to adopt healthy lifestyles in the long term.

Sensitivity analysis results

In the 2014–2018 subset analyses the protective and lagged effects of HL→CDs persisted (β_4=-0.515, β_5=-0.257, all $P < 0.001$), while the negative effect of CDs→HL was non-significant (β_6=-0.011, β_7=-0.561, all $P > 0.05$; CFI = 0.984, TLI = 0.956, RMSEA = 0.03). Furthermore, the inclusion of the lockdown index as a covariate in the full model exhibited that the positive effect of HL→CDs was still significant from 2014 to 2018 (β_8=-0.024, β_9=-0.058, all $P < 0.001$), and it was still an effect reversal of CDs→HL from 2018 to 2020 (β_{10}=-0.011, $P_{10} < 0.001$; CFI = 0.930, TLI = 0.906, RMSEA = 0.03), indicating robustness to pandemic-related confounding. Meanwhile, using inverse probability weighting to re-adjust the weight and conduct RI-CLPM analysis also did not alter the direction of effects, and none of the result changed significance (see supplementary material Table S4).

Discussion

While previous investigations have examined associations between healthy lifestyles and chronic diseases, some limitations persist in current evidence. Prior studies employing cross-sectional designs or static models have inadequately captured the temporal reciprocity and developmental trajectories inherent in lifestyle-disease interactions, particularly regarding multimorbidity progression in aging populations [12, 15, 19, 20]. The RI-CLPM can disentangle within-person dynamics from between-person heterogeneity, better capture the evolution relationship between variables, and gradually applied to the field of public health [48–50]. It offers novel insights into how lifestyles and chronic diseases progression reciprocally influence each other over time, a dimension underexplored in prior studies. Our study innovatively addresses these gaps by implementing RI-CLPM to analyze longitudinal data from middle-aged and older Chinese, systematically examining dynamic relationships between healthy lifestyles and multimorbidity in 2014–2020. This methodological advancement enables precise estimation of cross-lagged effects-quantifying the association between healthy lifestyles and diseases status-while controlling for stable interindividual differences.

Existing epidemiological evidence has demonstrated that adopting healthy lifestyles, such as regular physical exercise, smoking cessation, alcohol moderation, and adequate sleep, can significantly delay the progression of chronic diseases and improve health outcomes in middle-aged and older adults [14, 51]. Our findings align with these established insights, besides extend them by revealing a critical dynamic transition in diseases trajectories and lifestyle interactions among aging populations. By capturing dynamic shifts in effect directionality and magnitude across waves, we observed a pronounced transition toward multimorbidity, with its prevalence soaring from 9.2% (2014) to 29.1% (2020). Notably, 19.9% (n = 1,361) of the 6,852 participants transitioned toward multimorbidity during 2014–2020, slightly exceeding the 17.9% (n = 1,228) who shifted to single chronic disease. This tendency underscores the growing complexity of health challenges in aging cohorts. Additionally, our analysis uncovered a striking reversal in the protective role of healthy lifestyles post-2018. Initially, healthier lifestyles delayed diseases progression, however, as time elapsed and the aggravation of chronic diseases status, the protective effect of healthy lifestyles was gradually offset and reversed in 2018. The more severe diseases status (e.g., multimorbidity), the lower healthy lifestyles scores and less likely to choose health behavior, suggesting a feedback loop of the low holding rate of health lifestyles and worsening chronic disease burden. This reversal coincides with China's accelerated aging process and persistent urban-rural healthcare disparities, which amplify biological and psychological declines through synergistic pathways. Our results resonate with global trends of rising multimorbidity in aging populations and highlight time-sensitive intervention windows critical to China's Healthy Aging 2030 agenda. Specifically, we emphasize the need for context-specific strategies to enhance midlife lifestyle interventions, as these may mitigate chronic diseases incidence and extend healthy longevity—while addressing the shifting dynamics of lifestyle-disease interactions observed in later phases of aging.

Biological and psychosocial pathways of Multimorbidity progression

The accelerated transition to multimorbidity and the reversal of cross-lagged effect in later stages align with global evidence on synergistic biological-psychological cascades [52]. For instance, Barnett et al.(2012) demonstrated that chronic diseases such as hypertension or diabetes, trigger systemic inflammation and metabolic dysregulation, fostering physiological vulnerabilities for secondary diseases through shared pathways like oxidative stress, mitochondrial dysfunction, and insulin resistance—a mechanism corroborated in our cohort [6]. Some studies highlight the role of epigenetic aging and cellular senescence in accelerating these processes, particularly in populations with prolonged exposure to lifestyle-related risk factors [53–56]. For instance, elevated DNA methylation age (DNAmAge) has been linked to faster progression from single chronic diseases to multimorbidity, underscoring the interplay between biological aging and behavioral factors [57]. Concurrently, disease-related functional limitations and psychological burden (e.g., depression, anxiety, and cognitive load from complex self-care regimens) erode self-efficacy for maintaining healthy behaviors [58]. This phenomenon is amplified by China's sociocultural context, where familial caregiving roles often prioritize collective well-being over individual health autonomy [58, 59]. Aging individuals who internalize perceptions of being a "burden" may experience diminished motivation for proactive health management, perpetuating a self-reinforcing cycle of disease progression and behavioral inertia. These dynamics are in line with Bandura's self-efficacy theory [60, 61]wherein diminished belief in personal capabilities predicts reduced health behavior adherence to health-promoting behaviors. Notably, some studies revealed that low self-efficacy mediates the association between multimorbidity and poor lifestyle adherence, and indirectly affected health adherence through social support [62, 63]. To address these pathways, interventions must integrate biological and psychosocial strategies. For example, anti-inflammatory diets (e.g., Mediterranean or Dietary approaches to stop hypertension diets) combined with mindfulness-based stress reduction (MBSR) programs could simultaneously mitigate metabolic dysregulation and enhance self-efficacy. We could adapt these models to China's context—for instance, incorporating traditional Chinese medicine (TCM) dietary principles or Tai Chi-based mindfulness—could enhance cultural scalability and promote health adherence.

Time-sensitive intervention windows

The result of subgroup analysis demonstrated that the priority groups of chronic disease health intervention were women, rural areas and the older. And the reversal of cross-lagged effects post-2018 underscores temporally distinct critical phases for intervention, offering novel insights into the interplay between aging, lifestyles and chronic diseases. The protective effects of healthy lifestyles from 2014 to 2018 indicate a "time-sensitive window" for early intervention phase, during which group-based lifestyle coaching could capitalize on neuroplasticity and behavioral habit formation. Neuroimaging studies suggest that middle-aged adults retain significant capacity for habit formation via prefrontal cortex engagement, whereas older adults increasingly rely on basal ganglia circuits associated with entrenched behaviors [64–66]. Thus, early interventions targeting women, rural areas and the middle-aged, could leverage this neuroplasticity through structured programs like the WHO "Integrated Care for Older People" (ICOPE), adapted to emphasize lifestyle modification [67]. Conversely, the attenuated effect observed in 2018–2020 reflects accumulated biological damage and psychological fatigue, necessitating tertiary interventions that integrate clinical care with behavioral economics principles. For instance, "commitment contracts" offering incremental rewards (e.g., subsidized health insurance premiums for meeting exercise goals) may counteract present bias—a tendency to prioritize immediate gratification over long-term benefits—common in chronic diseases patients [68]. This approach harnesses Confucian familial values by involving family members as accountability partners, thereby aligning individual health goals with cultural norms of collective responsibility. Furthermore, digital health technologies offer untapped potential for sustaining behavior change across these phases. Mobile health (mHealth) equipped with artificial intelligence(AI)-driven personalized feedback, such as real-time activity tracking or dietary logging, has become increasingly popular for the self-management of chronic diseases because of its high efficacy, accessibility, and cost-effectiveness and is defined by the WHO as the use of mobile and wireless devices to support healthcare management [69–72]. However, in China's context, optimizing these tools requires addressing digital literacy gaps, particularly the elderly population in rural areas. Simplified interfaces, voice-based interactions, and integration with ubiquitous platforms like WeChat Mini Programs could enhance accessibility. An intervention study utilizing WeChat Mini Programs for diabetes management revealed that the WeChat mini-program blood glucose management model can reduce two-hour postprandial glucose and improve the self-management ability, which verified the feasibility and effectiveness of the blood glucose management model relying on the WeChat mini-program [73].

System-level strategies for china's urban-rural divide

Our subgroup analysis found that the chronic diseases status of middle-aged and older Chinese was different between urban and rural areas ($P<0.05$). The urban-rural disparity in lifestyle-disease dynamics demands structural reforms grounded in China's unique epidemiological transition. Rural residents face a "triple jeopardy": limited healthcare access, low health literacy, and occupational hazards tied to agriculture [74]. These inequities are compounded by regional variations in healthcare infrastructure—for example, rural clinics often lack capacity for multimorbidity management, relying on outdated protocols focused on single-disease treatment. To address these inequities, we propose a three-tiered intervention model. First, village health workers could deliver simplified sleep hygiene and smoking cessation programs through culturally resonant mediums. For instance, dialect-specific videos or folk songs could disseminate messages about the dangers of late-night screen time or tobacco use. Second, township clinics might implement group medical visits combining traditional Chinese medicine modalities with chronic diseases management. Tai Chi sessions, for example, could serve dual purposes: promoting physical exercise and providing a platform for peer support and health education. Third, county hospitals could establish telemedicine hubs for multimorbidity care, integrated with provincial specialist networks [60, 75]. These hubs could utilize AI-powered diagnostic tools (e.g., retinal imaging for diabetic retinopathy screening) to bridge specialist shortages.

Policy integration and global implications

Our findings resonate with global trends but highlight context-specific nuances. The extant research demonstrates that in some LMICs, the progression of multimorbidity is more complex, and the health literacy is inadequate and needs to be improved the self-management [7, 76–80]. Meanwhile, some high-income countries with universal healthcare access report slower multimorbidity trajectories due to preventive screening programs, and early diseases detection, which mitigates diseases progression. For instance, the United Kingdom National Health Service (NHS) "Health Check" program—a universal screening initiative for adults aged 40–74—has reduced multimorbidity incidence through early detection and lifestyle counseling [77]. Therefore, China could adopt a phased approach, prioritizing high-risk regions (e.g., provinces with aging indices or the prevalence of multimorbidity above the national average) for targeted intervention campaigns. However, our findings emphasize that effective management of aging-related health challenges in LMICs like China requires a dual focus: biomedical interventions to address chronic diseases and structural reforms to tackle systemic barriers (digital divides, urban-rural healthcare disparities). Direct replication in China is challenged by urban-rural disparities and workforce shortages. Therefore, China could adopt a phased approach, prioritizing high-risk regions (e.g., provinces with aging indices or the prevalence of multimorbidity above the national average) for targeted intervention campaigns.

China's "Healthy China 2030" framework offers a strategic opportunity that bridges top-down policy directives with community-level innovation. For example, the government could launch the "National Demonstration Zones for Healthy Aging" initiative, and operationalize this vision by designating select community health service centers as a testing ground for the three-tiered intervention model proposed above. Such zones would receive targeted funding and human resources to implement tailored strategies, such as promoting healthy lifestyles, enhancing early disease detection, and integrating multidisciplinary care for aging populations. This approach mirrors the success of Brazil's Family Health Strategy but is adapted to address the unique challenges of aging societies, including multimorbidity and healthcare inequities. These zones could serve as a blueprint for LMICs where demographic aging outpaces healthcare modernization, aligning with the WHO's "Decade of Healthy Aging 2021–2030" priorities.

Conclusion

Our findings underscore the dynamic cross-lagged effects between healthy lifestyles and multimorbidity progression among middle-aged and older Chinese, influenced by biological-psychological cascades, low self-efficacy, and urban-rural healthcare disparities. The increased risk of transitioning to multimorbidity and the potential reversal of the positive effects of healthy lifestyles highlight the need for life-course interventions that adapt to the reciprocity between biological aging and health behaviors. We advocate the combination of dietary principles and exercise patterns for TCM, integrating behavioral economics into health incentives, leveraging digital health technology to drive health behavior, and the three-level intervention model to reduce urban-rural health inequities. By aligning individual-level motivation strategies with system-level resource redistribution, we hope to provide some references to firmly establish the proactive health concept of "being the first responsible person for health" and contribute to achieving healthy aging in China.

Limitations and strengths

Our article has some limitations. Firstly, the hours of spent in deep sleep, duration of overall sleep, or daytime tiredness are the factors influencing sleep quality and health outcomes [81]; however, the CFPS lacks relevant questions or replaceable indicators on these aspects, leading to an incomplete assessment of sleep time. Secondly, we restricted the sample to participants with complete four-phase follow-up data. While we used IPW as a sensitivity analysis to mitigate potential bias from non-random missing data, this may limit the generalization of our conclusions. Thirdly, the CFPS considers the "duration of each physical exercise ≥ 30 minutes" as an effective exercise to ensure comparability with international benchmarks, but we couldn't find the information on physical exercise type (e.g., running) or physiological metrics (e.g., heart rate) and couldn't directly compute metabolic equivalent. Finally, regional economic disparities and geospatial healthcare accessibility metrics were not completely controlled in our analysis and should be considered in future studies. Meanwhile, we plan to include more accurate missing data processing research methods, explore the composite index of healthy lifestyles assessment, and strive to assess the association more comprehensively between healthy lifestyles and chronic diseases, and enhance the robustness and generalization of the conclusions in the future studies.

This study also has some strengths. Firstly, it follows a nationally representative cohort study design and includes middle-aged and older people who are susceptible to chronic diseases. This is among the first studies to investigate the dynamic trajectory of chronic diseases status transition and the cross-lagged effect between healthy lifestyles and multimorbidity. Secondly, we use the RI-CLPM approach to disentangle within-person dynamics from population heterogeneity, revealing temporal nuances in lifestyle-disease interplay that are often obscured by traditional models. Finally, as the first longitudinal analysis of multimorbidity transition and cross-lagged effect in China's aging population, this study provides empirical grounding for national policies, and also provides a reference for LMICs to cope with the similar challenges.

Abbreviations

CFPS	China Family Panel Studies
RI-CLPM	Random intercept cross-lagged panel model
HL	Healthy lifestyles
CDs	Chronic diseases status
WHO	World Health Organization
IPW	Inverse Probability Weighting
TCM	Traditional Chinese medicine
LMICs	Low- and middle-income countries

Supplementary Information

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Supplementary Material 1: Fig. S1. Flowchart of this study population. Table S1. Comparison of physical exercise frequency items. Table S2. The description and assignment of variables. Table S3. Total number and percentages of chronic diseases status transition in 2014–2020 (n = 6,852). Table S4. Comparison of original results and incorporated inverse probability weighted results between healthy lifestyles and chronic diseases status.

Author contributions

X. Z. designed the study, contributed to the literature search, conducted the analysis and wrote the manuscript; H. M. and H. Z. conducted data acquisition, cleaning and analysis; Y. Z. critically revised the manuscript; S. T. obtained project funding; J. X. designed the research, contributed to the literature search and obtained project funding. All authors contributed to result interpretation and critical revision of the manuscript. All authors read and approved the final manuscript.

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Data availability

The data that support the findings of our study are available from China Family Panel Studies (CFPS) but restrictions apply to the availability of these data, which were used under license for the current study, and are not publicly available. Data are available from the corresponding author upon reasonable request, and with permission of CFPS, http://www.isss.pku.edu.cn/cfps or https://opendata.pku.edu.cn/dataverse/CFPS.

Declarations

Ethics approval and consent to participate

The China Family Panel Studies is a longitudinal survey implemented by the China Social Science Survey Center of Peking University. It was approved by the Ethical Review Committee of Peking University (IRB00001052-14010). All respondents have provided informed consent, and the study adhered to the principles of the Declaration of Helsinki.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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