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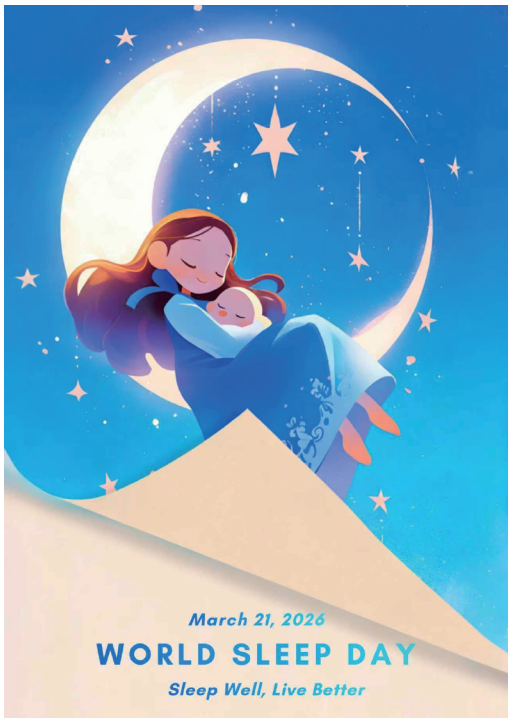

WORLD SLEEP DAY ISSUE

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Cover Image: adapted from Chinese Sleep Research Society.
This week's issue was organized by Guest Editor Shiwei Liu.

Perspectives

Sleep Health: A New Frontier for Public Health

Ding Zou[1,#]; Shiwei Liu[2]

ABSTRACT

Sleep is a fundamental biological necessity that remains underrecognized in global health policy. This perspective argues that sleep health constitutes a core pillar of public health and a key determinant of health equity. Moving beyond a deficit-based focus on clinical sleep disorders, a holistic sleep health framework highlights the social, environmental, and structural factors shaping population sleep patterns. Incorporating multidimensional sleep metrics into population health surveillance and public health agendas, aligned with the American Heart Association's Life's Essential 8 and the calls from the World Sleep Society Global Sleep Health Taskforce, can help address the "sleep gap" in society. Prioritizing sleep health is therefore essential to reducing chronic disease burden and improving population-level resilience and health outcomes.

This perspective paper synthesizes current scientific evidence to argue that sleep health is not merely a matter of individual wellness, but a foundational pillar of public health and a key driver of health equity. By shifting from a narrow emphasis on clinical sleep disorders to a holistic public health framework, sleep health can be more effectively integrated into population-level strategies, strengthening chronic disease prevention and management.

Biological Foundation of Sleep and Circadian Health

The biological need for sleep is rooted in the circadian system, a highly conserved evolutionary mechanism that synchronizes internal physiology with the 24-hour light-dark cycle. Research underscores that the circadian clock acts as a central regulator of cardiac function and metabolic homeostasis. This internal timing system governs rhythmic fluctuations in blood pressure, heart rate, vascular tone, and hormone secretion. When these rhythms are disrupted, whether through shift work, sleep deprivation, or irregular behaviors, cellular oscillators become misaligned, triggering pathogenic pathways that lead to cardiovascular disease (CVD) (*1*).

The impact of sleep on the cardiovascular system is mediated through three primary systems: the autonomic nervous system, the metabolic system, and the immune system. Insufficient or disrupted sleep leads to sympathetic overactivity and the activation of inflammatory cascades.

Chronic sleep deficiency promotes the recruitment of inflammatory cells to the arterial walls, accelerating the development of atherosclerosis (*2*). Furthermore, sleep plays a pivotal role in "cardiovascular resilience", allowing the heart and blood vessels to recover from daily physiological stressors. Consequently, sleep health must be prioritized as a biological imperative in public health strategies, equivalent to traditional metrics like nutrition and physical activity.

From Sleep Disorders to Sleep Health

Historically, the medical community has viewed sleep through a "deficit-based" lens, focusing primarily on the diagnosis and treatment of specific disorders such as obstructive sleep apnea or insomnia. While identifying pathology is vital, this clinical approach often fails to address the sleep needs of the broader population. A paradigm shift toward "Sleep Health" provides a positive, holistic frame of reference (*3*). Sleep health is defined as a multidimensional pattern of sleep-wakefulness, adapted to individual, social, and environmental demands, that promotes physical and mental well-being (*3*–*4*).

The most widely accepted model for measuring sleep health is the RU-SATED framework (*3*,*5*), which evaluates six key dimensions:

Regularity: Consistency of bedtimes and wake times.

Satisfaction: Subjective sleep quality.

Alertness: Ability to sustain wakefulness during the day.

Timing: Alignment of sleep within the 24-hour cycle.

Efficiency: Ratio of time asleep to total time in bed.

Duration: Total sleep obtained within a 24-hour period.

Crucially, sleep health does not exist in isolation. A "translational neuroscience" perspective reveals that sleep is deeply embedded within its social and environmental context (*4*). Individual behaviors are shaped by societal structures — from labor laws and neighborhood safety to urban design. Adopting a contextual framework enables public health professionals to identify "upstream" determinants, such as light pollution and economic instability, that undermine optimal sleep.

Global Consensus and Clinical Evidence

Rapid societal transformation and urbanization have significantly challenged healthy sleep patterns. In the Chinese general population, sleep disturbances remain highly prevalent: a meta-analysis of 376,824 individuals reported a pooled prevalence of poor sleep quality of 19% (*6*), and the prevalence of insomnia symptoms and obstructive sleep apnea continue to rise (*7*). Reflecting sleep's importance as a fundamental determinant of population health, several international consensus statements have elevated its priority. In 2022, the American Heart Association (AHA) updated its cardiovascular health construct from "Life's Simple 7" to "Life's Essential 8" by adding sleep duration as a key metric (*8*). This inclusion signals that sleep is now recognized as equally influential in CVD risk as blood pressure or lipid levels. A subsequent AHA scientific statement further delineated multidimensional sleep health — encompassing sleep duration, continuity, timing, regularity, sleep-related daytime functioning, architecture, and the absence of sleep disorders — and its relevance to cardiometabolic health (*9*). The AHA has also highlighted links between disturbed sleep and adverse neurological outcomes, including stroke, subclinical cerebrovascular disease, and Alzheimer's disease (*10*), and has emphasized circadian health as a critical component of metabolic well-being (*11*).

The World Sleep Society Global Sleep Health Taskforce has similarly called for integrating sleep into national public health agendas (*12*), arguing that the current neglect of sleep health — particularly in developing countries — constitutes a critical gap in global health policy. In Europe, an eight-component sleep health model incorporating additional domains related to breathing and disordered sleep has been proposed (Figure 1) (*13*). Ongoing efforts aim to synthesize data on the relationships between multidimensional sleep health, mortality, cardiovascular outcomes, and the socioeconomic impact of untreated sleep conditions (*14*). The recently released European Commission "Safe Hearts Plan" marks another milestone, advocating for the integration of sleep assessment into preventive care and public health monitoring across regional health systems.

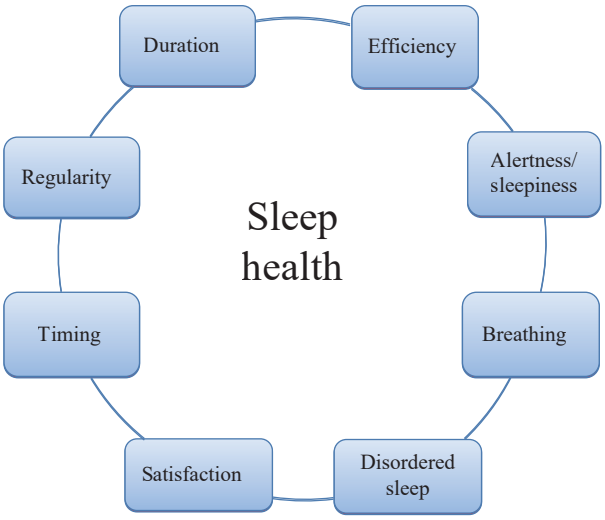

FIGURE 1. Multidimensional sleep health framework.

A growing body of longitudinal evidence supports the transition to a multidimensional sleep health framework. Studies demonstrate that "healthy sleep scores," which aggregate multiple sleep dimensions, outperform single metrics such as sleep duration in predicting cardiovascular risk (*15*). Tracking changes in these composite scores over time enables clinicians and public health officials to monitor shifts in population risk profiles. Notably, individuals who maintain or improve their sleep health scores exhibit significantly lower incidence of coronary heart disease and stroke.

Beyond physical health, sleep health is a major determinant of economic and functional outcomes. Recent studies have examined the relationship between multidimensional sleep health and work productivity, particularly among individuals with chronic conditions (*16*). In populations living with neurological disorders, poor sleep health — characterized by high fragmentation and low satisfaction — emerges as a significant predictor of reduced work performance and increased absenteeism. These findings suggest that promoting sleep health represents not only a medical imperative but also a strategy for enhancing societal productivity and reducing the economic burden of chronic illness.

Future Perspectives

It is evident that sleep health policies have begun to emerge in China. For example, sleep promotion has been incorporated into the Healthy China Action (2019–2030), which recommends an average daily sleep duration of 7–8 hours for adults and minimum sleep durations of 10, 9, and 8 hours for primary, junior high, and senior high school students, respectively. Nevertheless, additional efforts are required to further strengthen multidimensional sleep health promotion and advance health equity in China.

Currently, the "sleep gap" mirrors broader social inequalities: individuals from socially and economically marginalized backgrounds are disproportionately exposed to environmental stressors that degrade sleep quality (*17*). A socio-ecological framework is essential for addressing these disparities. This model recognizes that individual sleep is influenced by nested layers of influence: the social environment (e.g., family, work), the physical environment (e.g., noise, light), and the societal environment (e.g., policies). Looking forward, the research community has established a "roadmap" for the next decade of sleep health (*18*).

This roadmap prioritizes:

Mechanistic research: Understanding how sleep and circadian rhythms build "cardiovascular resilience" to protect against chronic stress.

Environmental policy: Advocating for structural changes, such as the regulation of blue light in public spaces and the implementation of "circadian-friendly" work schedules.

Holistic approach: Moving beyond individual-level sleep hygiene to implement structural and societal interventions that mitigate excessive work and social pressures and promote environments that support sufficient and high-quality sleep.

By treating sleep as a collective public health priority rather than an individual responsibility, we can close the sleep gap and improve health outcomes for the most vulnerable populations. Sleep is the new frontier for health equity, and its integration into the global public health agenda is no longer optional; it is essential for the future of human health.

Conflicts of interest: No conflicts of interest.

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Preplanned Studies

Sleep Patterns of Chinese Aged 15 and Above with Different Characteristics — China, 2024

Yingchen Sang[1]; Xinying Zeng[1]; Ying Liu[1]; Youjiao Wang[1]; Zhiping Peng[2]; Shiwei Liu[1,#]

Summary

What is already known about this topic?

Comprehensive data characterizing sleep patterns across China's diverse population remain scarce.

What is added by this report?

Among Chinese residents aged 15 years and older, this study found a mean sleep duration of 7.24 [95% confidence interval (*CI*): 7.16, 7.32] hours, a mean sleep latency of 27.45 (26.39, 28.51) minutes, a mean bedtime of 22:08 (21:58, 22:18), and a mean wake-up time of 6:18 (6:06, 6:30). Sleep patterns varied considerably across age groups and other demographic characteristics.

What are the implications for public health practice?

Rather than adopting uniform guidelines, public health interventions should implement tailored, context-specific sleep strategies that effectively address the distinct needs of diverse population groups.

ABSTRACT

Introduction: Sleep is fundamental to health, yet comprehensive data characterizing sleep patterns across China's diverse population remain scarce. This national study systematically assessed sleep behaviors among Chinese residents aged 15 years and above.

Methods: A population-based cross-sectional survey was conducted in 2024 among individuals aged 15 years and older, using multistage stratified cluster random sampling. Trained investigators collected data on sleep duration, sleep latency, bedtime, and wake-up time through standardized questionnaires. Statistical analyses incorporated sampling weights to ensure population representativeness, and stratified analyses examined sleep patterns across a range of demographic subgroups.

Results: The population-weighted mean sleep duration among Chinese residents aged 15 years and older was 7.24 [95% confidence interval (*CI*): 7.16, 7.32] hours in 2024. Mean bedtime and wake-up time were 22:08 (21:58, 22:18) and 6:18 (6:06, 6:30), respectively, with a mean sleep latency of 27.45 (26.39, 28.51) minutes. Age-stratified analyses revealed notable sex differences in sleep duration: among adults aged 18–44 years, females slept longer than males [7.66 (7.59, 7.73) hours versus 7.49 (7.41, 7.57) hours], whereas among those aged 45–64 years, females slept less [6.82 (6.72, 6.92) hours versus 6.97 (6.90, 7.04) hours]. Rural adolescents slept longer than their urban counterparts [8.39 (8.14, 8.64) hours versus 8.00 (7.78, 8.22) hours]. Both education level and occupation further influenced sleep duration and timing.

Conclusion: Sleep patterns among Chinese residents vary substantially by age, sex, and socio-environmental context. Effective sleep health strategies must be population-specific and tailored, rather than relying on uniform recommendations. Public health interventions should explicitly address the distinct socioeconomic and environmental determinants that shape sleep in different population segments, thereby optimizing sleep outcomes across diverse settings.

Sleep represents a fundamental pillar of health and well-being, yet population-level sleep characteristics remain incompletely understood, particularly in large and diverse populations such as China (*1*). Prior research has predominantly examined isolated metrics — either sleep duration or sleep quality — while the complex interrelationships among multiple sleep parameters, including timing and latency, remain poorly characterized (*2*). This knowledge gap impedes the development of effective, evidence-based sleep health interventions. To address this gap, this study conducted a nationally representative survey comprehensively assessing sleep patterns among Chinese residents aged 15 years and above, with particular attention to variation across demographic subgroups defined by sex, urban or rural residence,

educational attainment, and occupation. The findings offer a foundation for developing tailored, evidence-based strategies for sleep health promotion that account for the multidimensional nature of sleep behavior across diverse population contexts.

This survey employed a multistage stratified cluster sampling design to recruit a sample representative of China's general adult population, excluding military personnel and institutionalized individuals. Eligibility required at least one month of continuous residence at the current address; individuals residing in student dormitories, military barracks, correctional facilities, or hospitals were ineligible. The sampling procedure comprised five stages. First, one provincial-level administrative division (PLAD) was randomly selected from each of China's seven major geographical regions (North China: Hebei; Northeast China: Liaoning; East China: Jiangsu; Central China: Henan; South China: Guangdong; Southwest China: Chongqing; Northwest China: Shaanxi). Second, probability proportional to size (PPS) sampling was used to select 10 county-level administrative divisions within each PLAD, which served as primary sampling units (PSUs). Third, three districts (urban areas) or townships (rural areas) were selected from each PSU using PPS. Fourth, two communities or villages were selected from each district or township. Fifth, simple random sampling was used to recruit 120 households from each district or township, and one individual aged 15 years or older was then randomly selected from each household. Data collection took place from June to November 2024. All participants provided informed consent electronically prior to participation. The institutional review board of the Chinese Center for Disease Control and Prevention approved the study protocol (approval number 202410).

In this study, "sleep patterns" refers to the multidimensional behavioral characteristics of an individual's daily sleep–wake cycle. These patterns were quantified through standardized questionnaires capturing four self-reported macroscopic metrics. Sleep duration was assessed using the question "During the past month, how many hours of actual sleep did you get at night?", representing average nightly nocturnal sleep — excluding naps — over the preceding month. Bedtime was ascertained from responses to "When have you usually gone to bed?" and wake-up time from "When have you usually gotten up in the morning?" Sleep latency was derived from "How long (in minutes) has it taken you to fall asleep each night?"

To account for the complex multistage stratified sampling design, a comprehensive weighting strategy was implemented to ensure that results were representative of the community-dwelling population aged 15 years and above across the study regions. The final sampling weights were constructed as the product of three components: 1) base weight, derived from the inverse of the selection probabilities at each sampling stage; 2) non-response adjustment weight, calculated to compensate for individual-level non-participation; and 3) post-stratification weight, calibrated to the age, sex, and urban–rural distribution of the national population according to the 2020 Census. All statistical analyses incorporated these final weights to strengthen the population-level validity of the estimates. Normally distributed continuous variables were presented as means with 95% confidence intervals (*CI*s). Group comparisons were performed using t-tests or one-way analysis of variance (ANOVA) for normally distributed data. All analyses were conducted in SAS software (version 9.4, SAS Institute Inc., Cary, NC, USA) and R version 4.4.1. Statistical significance was defined as a two-tailed $P<0.05$.

In 2024, the weighted mean sleep duration among Chinese residents aged 15 years and above was 7.24 (95% *CI*: 7.16, 7.32) hours. The mean bedtime was 22:08 (21:58, 22:18), the mean wake-up time was 6:18 (6:06, 6:30), and the mean sleep latency was 27.45 (26.39, 28.51) minutes. Compared with males, females had significantly shorter sleep duration [7.21 (7.11, 7.31) hours versus 7.26 (7.19, 7.33) hours, $P=0.03$], earlier bedtimes [22:00 (21:51, 22:09) versus 22:16 (22:04, 22:28), $P<0.0001$], earlier wake-up times [6:12 (6:01, 6:23) versus 6:24 (6:12, 6:36), $P<0.0001$], and longer sleep latency [29.89 (28.53, 31.25) minutes versus 25.08 (24:13, 26:03) minutes, $P<0.0001$]. A clear age-related gradient was evident: compared with younger adults, older adults experienced progressively shorter sleep duration [from 8.21 (8.02, 8.40) hours to 6.79 (6.70, 6.88) hours], earlier sleep schedules [bedtime: from 22:41 (22:31, 22:51) to 21:10 (21:04, 21:16); wake-up time: from 7:48 (7:25, 8:11) to 5:10 (5:05, 5:15)], and longer sleep latency [from 25.33 (20.82, 29.84) minutes to 34.78 (32.95, 36.61) minutes]. Urban residents maintained later bedtimes [22:32 (22:19, 22:45) versus 21:49 (21:43, 21:55), $P<0.0001$] and wake-up times [6:39 (6:23, 6:55) versus 6:01 (5:54, 6:08), $P<0.0001$] than their rural counterparts, while also exhibiting shorter sleep latency [25.91 (24.62, 27.20) minutes versus 28.76 (27.54, 29.98) minutes, $P<0.0001$]. Geographically, residents of East China [7.11 (6.97, 7.25) hours] and North

China [7.11 (6.99, 7.23) hours] reported the shortest sleep durations, whereas those in South China reported the lowest sleep latency [25.50 (23.00, 28.00) minutes] and the latest sleep schedules [bedtime: 23:01 (22:53, 23:09); wake-up time: 7:05 (6:52, 7:18)]. Higher educational attainment was associated with later sleep schedules and notably shorter sleep latency. Certain occupations — particularly government or public institution staff and retirees — were associated with shorter sleep duration, while agricultural workers, retirees, and unemployed individuals tended toward earlier sleep schedules and longer sleep latency. Furthermore, current alcohol drinkers and ever-smokers experienced shorter sleep duration and earlier wake-up times compared with their respective counterparts (Table 1).

Age-stratified analyses revealed distinct sex-based patterns across different life stages. Among adolescents aged 15–17 years, no significant sex differences were observed in sleep duration, sleep latency, bedtime, or wake-up time. In the 18–64 age group, females consistently demonstrated longer sleep latency and earlier sleep schedules than males. Sleep duration patterns, however, diverged by age subgroup: females aged 18–44 years slept significantly longer than males [7.66 (7.59, 7.73) hours versus 7.49 (7.41, 7.57) hours], whereas females aged 45–64 years slept significantly less than their male counterparts [6.82 (6.72, 6.92) hours versus 6.97 (6.90, 7.04) hours]. Urban–rural comparisons revealed that rural adolescents aged 15–17 years slept substantially longer than urban peers [8.39 (8.14, 8.64) hours versus 8.00 (7.78, 8.22) hours], though this difference was not apparent in older age groups. Among individuals aged 18 years and above, urban residents consistently maintained later sleep schedules than rural residents. Educational attainment correlated positively with sleep duration in the 18–64 age group, and higher education levels were associated with progressively later sleep schedules across all adult age groups (18+ years). Occupational patterns showed notable variation: among those aged 18–44 years, students achieved the longest sleep duration [8.40 (8.28, 8.52) hours], while retirees [6.69 (6.54, 6.84) hours] and government or public institution staff [7.07 (6.85, 7.29) hours] reported the shortest. Agricultural workers consistently exhibited the earliest sleep schedules [bedtime: 21:50 (21:41, 21:59); wake-up time: 6:12 (6:04, 6:20)]. Among those aged 65 years and above, teachers demonstrated both the longest sleep duration [7.52 (7.01, 8.03) hours] and the shortest sleep latency [19.25 (16.05, 22.45) minutes], while agricultural workers maintained their characteristically early sleep schedules [bedtime: 20:59 (20:53, 21:05); wake-up time: 5:02 (4:57, 5:07)] (Table 2).

DISCUSSION

This study characterized sleep duration and patterns among Chinese residents aged 15 years and older, yielding a weighted mean sleep duration of 7.24 [95% *CI*: 7.16, 7.32] hours. Prior research reported mean sleep durations of 7.38±1.37 hours among adults aged 30–79 between 2004 and 2008 (*3*), and 7.56±1.82 hours among adults aged 18 and older in the China Family Panel Studies (*4*). By comparison, the findings suggest a modest yet discernible downward trend in sleep duration over the past decade. Although an absolute decline of approximately 8 to 19 minutes may appear small, such a shift at the population level carries meaningful public health implications. This trend likely reflects the accelerating pace of modern life, intensifying socioeconomic competition, and the pervasive use of electronic devices — factors that collectively erode nocturnal sleep opportunity (*5*), rather than indicating temporal stability in population-level sleep behavior.

The findings also revealed distinct sociological patterning of sleep behaviors across demographic subgroups. Because physiological, social, and environmental factors shape sleep needs differently across the life course, notable variation emerges by age and sex. Among individuals aged 18–44, women slept longer than men on average, yet reported greater sleep latency and earlier bedtimes. This pattern may reflect the dual burden of occupational demands and domestic responsibilities that disproportionately falls on women (*6*), heightening pre-sleep cognitive arousal and thereby prolonging sleep onset. Earlier bedtimes, in turn, may represent a compensatory strategy to secure adequate rest despite competing pressures — particularly those associated with childcare and household management (*7*). Thus, the longer sleep durations observed in younger women likely stem from earlier sleep initiation as an offset against chronic sleep insufficiency. Among women aged 45–64, however, this pattern reversed: women in this group slept less than their male counterparts. This reversal may reflect the convergence of menopausal hormonal changes, peak career pressures, and shifting family roles — circumstances that collectively compromise sleep duration during this life stage (*8*).

TABLE 1. Sleep patterns of Chinese aged 15 and above with different characteristics — China, 2024.

Characteristics	Overall *N* (%)	Sleep duration $\bar{x}$ (hours) (95% *CI*)	*P*	Sleep latency $\bar{x}$ (min) (95% *CI*)	*P*	Bedtime $\bar{x}$ (95% *CI*)	*P*	Wake-up time $\bar{x}$ (95% *CI*)	*P*
Total	46,207 (100)	7.24 (7.16, 7.32)		27.45 (26.39, 28.51)		22:08 (21:58, 22:18)		6:18 (6:06, 6:30)	
Sex			0.03		<0.0001		<0.0001		<0.0001
Male	22,334 (48.33)	7.26 (7.19, 7.33)		25.08 (24.13, 26.03)		22:16 (22:04, 22:28)		6:24 (6:12, 6:36)	
Female	23,873 (51.67)	7.21 (7.11, 7.31)		29.89 (28.53, 31.25)		22:00 (21:51, 22:09)		6:12 (6:01, 6:23)	
Age, years			<0.0001		<0.0001		<0.0001		<0.0001
15–17	477 (4.28)	8.21 (8.02, 8.40)		25.33 (20.82, 29.84)		22:41 (22:31, 22:51)		7:48 (7:25, 8:11)	
18–44	11,416 (45.03)	7.57 (7.51, 7.63)		24.72 (23.67, 25.77)		22:38 (22:26, 22:50)		7:10 (7:02, 7:18)	
45–64	19,822 (34.42)	6.89 (6.82, 6.96)		27.83 (26.74, 28.92)		21:53 (21:47, 22:00)		6:05 (5:58, 6:12)	
≥65	14,492 (16.27)	6.79 (6.70, 6.88)		34.78 (32.95, 36.61)		21:10 (21:04, 21:16)		5:10 (5:05, 5:15)	
Residence			0.16		0.002		<0.0001		<0.0001
Urban	24,912 (53.91)	7.30 (7.18, 7.42)		25.91 (24.62, 27.20)		22:32 (22:19, 22:45)		6:39 (6:23, 6:55)	
Rural	21,295 (46.09)	7.19 (7.09, 7.29)		28.76 (27.54, 29.98)		21:49 (21:43, 21:55)		6:01 (5:54, 6:08)	
National region			<0.05		0.004		<0.0001		<0.0001
North China	6,864 (14.85)	7.11 (6.99, 7.23)		27.12 (25.95, 28.29)		22:02 (21:52, 22:12)		5:58 (5:45, 6:11)	
Northeast China	6,429 (13.91)	7.15 (7.08, 7.22)		26.12 (24.66, 27.58)		21:35 (21:21, 21:49)		5:36 (5:21, 5:51)	
East China	6,584 (14.25)	7.11 (6.97, 7.25)		27.90 (25.47, 30.33)		21:43 (21:26, 22:00)		6:33 (6:15, 6:51)	
Central China	6,677 (14.45)	7.40 (7.23, 7.57)		29.64 (28.07, 31.21)		21:42 (21:24, 22:00)		6:07 (5:47, 6:27)	
South China	6,551 (14.18)	7.27 (7.04, 7.50)		25.50 (23.00, 28.00)		23:01 (22:53, 23:09)		7:05 (6:52, 7:18)	
Southwest China	6,423 (13.90)	7.22 (7.03, 7.41)		29.95 (28.23, 31.67)		22:10 (21:52, 22:28)		6:25 (6:08, 6:42)	
Northwest China	6,679 (14.45)	7.40 (7.15, 7.65)		27.53 (24.09, 30.97)		22:12 (21:56, 22:28)		6:29 (6:15, 6:43)	
Education level			<0.0001		<0.0001		<0.0001		<0.0001
Primary school or below	15,531 (33.61)	6.83 (6.74, 6.92)		33.75 (32.02, 35.48)		21:21 (21:15, 21:27)		5:22 (5:17, 5:27)	
Junior high school	16,678 (36.09)	7.21 (7.13, 7.29)		26.64 (25.53, 27.75)		22:00 (21:53, 22:07)		6:08 (6:01, 6:15)	
High school/vocational school	6,876 (14.88)	7.44 (7.34, 7.54)		25.43 (24.25, 26.61)		22:26 (22:15, 22:37)		6:43 (6:30, 6:56)	
University/college or above	7,024 (15.20)	7.48 (7.40, 7.56)		24.55 (23.32, 25.78)		22:48 (22:37, 23:00)		7:03 (6:53, 7:13)	
Unknown	98 (0.21)	8.03 (7.73, 8.33)		23.95 (20.83, 27.07)		22:32 (22:02, 23:02)		7:28 (6:48, 8:08)	
Occupation			<0.0001		<0.0001		<0.0001		<0.0001
Agricultural workers	16,513 (35.74)	7.01 (6.89, 7.13)		29.84 (28.27, 31.41)		21:25 (21:19, 21:31)		5:28 (5:22, 5:34)	

Continued

Characteristics	Overall *N* (%)	Sleep duration $\bar{x}$ (hours) (95% *CI*)	*P*	Sleep latency $\bar{x}$ (min) (95% *CI*)	*P*	Bedtime $\bar{x}$ (95% *CI*)	*P*	Wake-up time $\bar{x}$ (95% *CI*)	*P*
Government/public institution staff	914 (1.98)	6.99 (6.81, 7.17)		25.89 (23.78, 28.00)		22:49 (22:36, 23:02)		6:37 (6:28, 6:46)	
Business/service employee	7,558 (16.36)	7.26 (7.15, 7.37)		24.72 (23.59, 25.85)		22:33 (22:20, 22:46)		6:37 (6:22, 6:52)	
Teaching staff	582 (1.26)	7.45 (7.29, 7.61)		24.22 (22.82, 25.62)		22:34 (22:23, 22:45)		6:47 (6:34, 7:00)	
Medical/health personnel	553 (1.20)	7.42 (7.30, 7.54)		24.43 (22.95, 25.91)		22:30 (22:21, 22:39)		6:37 (6:32, 6:42)	
Students	1,013 (2.19)	8.29 (8.16, 8.42)		23.67 (20.98, 26.36)		22:49 (22:38, 23:00)		7:53 (7:42, 8:04)	
Unemployed	5,656 (12.24)	7.24 (7.11, 7.37)		32.49 (30.48, 34.50)		21:52 (21:41, 22:03)		6:12 (6:00, 6:24)	
Retired	5,336 (11.55)	6.81 (6.68, 6.94)		29.72 (27.14, 32.30)		21:42 (21:30, 21:54)		5:34 (5:22, 5:46)	
Others	7,737 (16.74)	7.20 (7.10, 7.30)		26.70 (25.15, 28.25)		22:23 (22:09, 22:37)		6:28 (6:14, 6:42)	
Unknown	345 (0.75)	7.62 (7.40, 7.84)		22.06 (19.50, 24.62)		22:28 (22:13, 22:43)		6:51 (6:36, 7:06)	
Drink			<0.0001		0.84		0.86		0.0001
No	40,564 (87.79)	7.28 (7.20, 7.36)		27.47 (26.42, 28.52)		22:08 (21:57, 22:19)		6:20 (6:09, 6:31)	
Yes	5,643 (12.21)	6.91 (6.83, 6.99)		27.31 (25.45, 29.17)		22:08 (21:56, 22:20)		6:02 (5:48, 6:16)	
Smoking status			<0.0001		0.001		<0.0001		<0.0001
Never smoker	31,763 (68.75)	7.32 (7.23, 7.41)		27.83 (26.54, 29.12)		22:08 (21:57, 22:19)		6:22 (6:10, 6:34)	
Current smoker	10,358 (22.42)	7.08 (7.01, 7.15)		25.87 (24.91, 26.83)		22:17 (22:08, 22:26)		6:17 (6:07, 6:27)	
Former smoker	4,081 (8.83)	6.90 (6.81, 6.99)		28.81 (27.35, 30.27)		21:46 (21:36, 21:56)		5:39 (5:29, 5:49)	

Note: Regions were divided based on China's seven major geographic regions, including North China (Hebei), Northeast China (Liaoning), East China (Jiangsu), Central China (Henan), South China (Guangdong), Southwest China (Chongqing), and Northwest China (Shaanxi). In the occupation category, "Others" refers to occupations not included in the specific categories listed, while "Unknown" indicates that the occupation information was unavailable or could not be determined.
Abbreviation: *CI*=confidence interval.

TABLE 2. Sleep patterns across sex, residence, education levels, and occupations in different age groups — China, 2024.

Age groups (years)	Characteristics	Total	Sleep duration $\bar{x}$ (hours) (95% *CI*)	*P*	Sleep latency $\bar{x}$ (min) (95% *CI*)	*P*	Bedtime $\bar{x}$ (95% *CI*)	*P*	Wake-up time $\bar{x}$ (95% *CI*)	*P*
15–17	Sex			0.81		0.15		0.55		0.38
	Male	263	8.19 (7.95, 8.43)		27.74 (20.15, 35.33)		22:42 (22:31, 22:53)		7:44 (7:07, 8:21)	
	Female	214	8.23 (7.96, 8.50)		21.99 (19.74, 24.24)		22:38 (22:26, 22:50)		7:54 (7:36, 8:12)	
	Residence			0.02		0.30		0.09		0.53
	Urban	256	8.00 (7.78, 8.22)		28.08 (18.76, 37.40)		22:48 (22:39, 22:57)		7:38 (6:56, 8:20)	
	Rural	221	8.39 (8.14, 8.64)		23.02 (20.37, 25.67)		22:34 (22:20, 22:48)		7:57 (7:32, 8:22)	

Continued

Age groups (years)	Characteristics	Total	Sleep duration $\bar{x}$ (hours) (95% CI)	P	Sleep latency $\bar{x}$ (min) (95% CI)	P	Bedtime $\bar{x}$ (95% CI)	P	Wake-up time $\bar{x}$ (95% CI)	P
	Education level			0.93		0.61		<0.0001		0.001
	Primary school or below	2	8.10 (7.93, 8.27)		22.93 (19.57, 26.29)		20:48 (20:28, 21:08)		6:37 (5:57, 7:17)	
	Junior high school	271	8.22 (7.94, 8.50)		23.59 (20.73, 26.45)		22:49 (22:35, 23:03)		7:44 (7:27, 8:01)	
	High school/ Vocational school	193	7.76 (7.66, 7.86)		24.05 (22.72, 25.38)		22:42 (22:29, 22:55)		7:16 (7:05, 7:27)	
	University/ College or above	7	8.19 (7.26, 9.12)		18.65 (9.66, 27.64)		21:56 (20:45, 23:07)		6:47 (6:19, 7:15)	
	Unknown	4	8.02 (6.90, 9.14)		22.84 (20.95, 24.73)		23:11 (22:45, 23:37)		8:21 (6:23, 10:19)	
	Occupation			<0.0001		0.47		<0.0001		0.46
	Agricultural workers	3	10.70 (9.36, 12.04)		21.33 (19.31, 23.35)		21:41 (21:01, 22:21)		9:45 (7:27, 12:03)	
	Government/ public institution staff	–	–		–		–		–	
	Business/ service employee	6	8.86 (8.37, 9.35)		21.07 (15.52, 26.62)		21:49 (20:10, 23:28)		7:25 (6:13, 8:37)	
	Teaching staff	–	–		–		–		–	
	Medical/health personnel	–	–		–		–		–	
	Students	442	8.17 (7.97, 8.37)		25.17 (20.32, 30.02)		22:42 (22:32, 22:52)		7:39 (7:26, 7:52)	
	Unemployed	11	8.42 (7.98, 8.86)		22.73 (15.27, 30.19)		22:39 (21:46, 23:32)		7:37 (6:37, 8:37)	
	Retired	–	–		–		–		–	
	Others	13	8.80 (8.01, 9.59)		35.53 (31.33, 39.73)		22:19 (21:47, 22:51)		8:13 (6:59, 9:27)	
	Unknown	2	8.00 (7.06, 8.94)		25.33 (20.93, 29.73)		22:40 (22:02, 23:18)		7:30 (7:30, 7:30)	
18–44	Sex			<0.0001		0.0004		<0.0001		0.001
	Male	5,203	7.49 (7.41, 7.57)		23.56 (22.30, 24.82)		22:50 (22:37, 23:03)		7:15 (7:02, 7:28)	
	Female	6,213	7.66 (7.59, 7.73)		25.96 (24.78, 27.14)		22:26 (22:15, 22:37)		7:04 (6:56, 7:12)	
	Area			0.83		0.12		<0.0001		<0.0001
	Urban	7,997	7.58 (7.53, 7.63)		24.02 (22.58, 25.46)		22:56 (22:44, 23:08)		7:14 (7:03, 7:25)	
	Rural	3,419	7.56 (7.44, 7.68)		25.52 (24.29, 26.75)		22:31 (22:22, 22:40)		7:05 (6:56, 7:14)	
	Education level			<0.0001		0.47		<0.0001		<0.0001
	Primary school or below	639	7.31 (7.09, 7.53)		26.48 (23.69, 29.27)		22:01 (21:45, 22:17)		6:22 (6:08, 6:36)	
	Junior high school	3,318	7.47 (7.38, 7.56)		25.30 (23.78, 26.82)		22:20 (22:11, 22:29)		6:40 (6:33, 6:47)	
	High school/ Vocational school	2,239	7.76 (7.66, 7.86)		24.05 (22.72, 25.38)		22:42 (22:29, 22:55)		7:16 (7:05, 7:27)	

Continued

Age groups (years)	Characteristics	Total	Sleep duration $\bar{x}$ (hours) (95% CI)	P	Sleep latency $\bar{x}$ (min) (95% CI)	P	Bedtime $\bar{x}$ (95% CI)	P	Wake-up time $\bar{x}$ (95% CI)	P
	University/ College or above	5,173	7.57 (7.50, 7.64)		24.48 (23.30, 25.66)		22:52 (22:40, 23:04)		7:12 (7:03, 7:21)	
	Unknown	47	8.23 (7.83, 8.63)		24.09 (20.07, 28.11)		22:55 (22:16, 23:34)		8:00 (7:15, 8:45)	
	Occupation			<0.0001		<0.0001		<0.0001		<0.0001
	Agricultural workers	1,466	7.56 (7.42, 7.70)		25.29 (23.34, 27.24)		21:50 (21:41, 21:59)		6:12 (6:04, 6:20)	
	Government/ public institution staff	531	7.07 (6.85, 7.29)		26.85 (24.55, 29.15)		22:57 (22:44, 23:10)		6:52 (6:42, 7:02)	
	Business/ service employee	3,932	7.43 (7.34, 7.52)		24.42 (23.06, 25.78)		22:44 (22:31, 22:57)		6:59 (6:46, 7:12)	
	Teaching staff	385	7.58 (7.40, 7.76)		23.87 (22.40, 25.34)		22:35 (22:23, 22:47)		6:57 (6:42, 7:12)	
	Medical/health personnel	373	7.51 (7.37, 7.65)		24.62 (22.95, 26.29)		22:32 (22:21, 22:43)		6:44 (6:38, 6:50)	
	Students	571	8.40 (8.28, 8.52)		22.17 (20.47, 23.87)		22:56 (22:41, 23:11)		8:06 (7:52, 8:20)	
	Unemployed	1,231	7.79 (7.64, 7.94)		27.24 (24.48, 30.00)		22:26 (22:13, 22:39)		7:12 (7:01, 7:23)	
	Retired	4	6.69 (6.54, 6.84)		26.14 (22.05, 30.23)		23:26 (23:15, 23:37)		6:43 (6:29, 6:57)	
	Others	2,757	7.48 (7.39, 7.57)		24.89 (23.23, 26.55)		22:48 (22:34, 23:02)		7:06 (6:54, 7:18)	
	Unknown	166	7.84 (7.59, 8.09)		19.94 (17.81, 22.07)		22:43 (22:29, 22:57)		7:13 (6:58, 7:28)	
45–64	Sex			<0.0001		<0.0001		<0.0001		<0.0001
	Male	9,538	6.97 (6.90, 7.04)		24.75 (23.85, 25.65)		21:57 (21:51, 22:03)		6:06 (5:58, 6:14)	
	Female	10,284	6.82 (6.72, 6.92)		30.90 (29.47, 32.33)		21:49 (21:44, 21:54)		6:05 (5:59, 6:11)	
	Area			0.19		0.004		<0.0001		<0.0001
	Urban	9,982	6.95 (6.83, 7.07)		26.17 (25.15, 27.19)		22:12 (22:05, 22:19)		6:22 (6:17, 6:27)	
	Rural	9,840	6.85 (6.76, 6.94)		29.01 (27.41, 30.61)		21:39 (21:34, 21:44)		5:54 (5:49, 5:59)	
	Education level			0.002		<0.0001		<0.0001		<0.0001
	Primary school or below	6,191	6.75 (6.65, 6.85)		31.88 (29.93, 33.83)		21:35 (21:29, 21:41)		5:26 (5:20, 5:32)	
	Junior high school	9,114	6.93 (6.84, 7.02)		26.93 (25.66, 28.20)		21:47 (21:42, 21:52)		5:40 (5:35, 5:45)	
	High school/ Vocational school	2,961	6.95 (6.88, 7.02)		25.17 (23.98, 26.36)		22:13 (22:05, 22:21)		5:59 (5:48, 6:10)	
	University/ College or above	1,533	7.01 (6.86, 7.16)		24.64 (22.54, 26.74)		22:36 (22:25, 22:47)		6:19 (6:09, 6:29)	
	Unknown	23	7.21 (6.71, 7.71)		25.33 (19.76, 30.90)		21:52 (21:12, 22:32)		6:02 (5:25, 6:39)	
	Occupation			0.48		<0.0001		<0.0001		<0.0001

Continued

Age groups (years)	Characteristics	Total	Sleep duration $\bar{x}$ (hours) (95% CI)	P	Sleep latency $\bar{x}$ (min) (95% CI)	P	Bedtime $\bar{x}$ (95% CI)	P	Wake-up time $\bar{x}$ (95% CI)	P
	Agricultural workers	8,177	6.88 (6.77, 6.99)		29.11 (27.62, 30.60)		21:29 (21:23, 21:35)		5:23 (5:17, 5:29)	
	Government/ public institution staff	359	6.79 (6.62, 6.96)		23.20 (20.02, 26.38)		22:33 (22:18, 22:48)		6:04 (5:52, 6:16)	
	Business/ service employee	3,281	6.89 (6.78, 7.00)		25.23 (24.09, 26.37)		22:12 (22:02, 22:22)		5:54 (5:41, 6:07)	
	Teaching staff	168	6.82 (6.68, 6.96)		25.96 (22.29, 29.63)		22:40 (22:29, 22:51)		6:10 (5:57, 6:23)	
	Medical/health personnel	160	7.20 (6.85, 7.55)		23.89 (21.50, 26.28)		22:22 (22:12, 22:32)		6:12 (5:59, 6:25)	
	Students	–	–		–		–		–	
	Unemployed	2,246	6.90 (6.71, 7.09)		32.95 (30.37, 35.53)		21:51 (21:43, 21:59)		5:50 (5:38, 6:02)	
	Retired	2,080	6.93 (6.80, 7.06)		27.61 (24.46, 30.76)		21:50 (21:38, 22:02)		5:46 (5:35, 5:57)	
	Others	3,257	6.89 (6.78, 7.00)		26.10 (24.70, 27.50)		22:09 (22:01, 22:17)		5:55 (5:47, 6:03)	
	Unknown	94	7.13 (6.65, 7.61)		26.06 (21.19, 30.93)		22:18 (21:52, 22:44)		6:21 (5:58, 6:44)	
≥65	Sex			<0.0001		<0.0001		0.34		0.04
	Male	7,330	6.96 (6.86, 7.06)		29.53 (28.11, 30.95)		21:11 (21:04, 21:18)		5:43 (5:38, 5:48)	
	Female	7,162	6.64 (6.54, 6.74)		39.49 (36.72, 42.26)		21:08 (21:01, 21:15)		5:46 (5:42, 5:50)	
	Area			0.40		0.07		<0.0001		0.003
	Urban	6,677	6.74 (6.62, 6.86)		32.64 (30.07, 35.21)		21:29 (21:21, 21:37)		5:54 (5:46, 6:02)	
	Rural	7,815	6.82 (6.69, 6.95)		35.88 (33.48, 38.28)		21:00 (20:52, 21:08)		5:39 (5:34, 5:44)	
	Education level			0.06		<0.0001		<0.0001		<0.0001
	Primary school or below	8,699	6.79 (6.68, 6.90)		37.40 (34.92, 39.88)		20:58 (20:51, 21:05)		5:05 (4:59, 5:11)	
	Junior high school	3,975	6.85 (6.76, 6.94)		31.34 (29.79, 32.89)		21:17 (21:10, 21:24)		5:14 (5:08, 5:20)	
	High school/ Vocational school	1,483	6.65 (6.53, 6.77)		30.81 (28.03, 33.59)		21:39 (21:30, 21:48)		5:22 (5:14, 5:30)	
	University/ College or above	311	6.75 (6.48, 7.02)		27.76 (23.71, 31.81)		22:00 (21:44, 22:16)		5:45 (5:34, 5:56)	
	Unknown	24	7.98 (6.44, 9.52)		22.65 (19.76, 25.54)		20:23 (19:18, 21:28)		5:06 (4:46, 5:26)	
	Occupation			0.0006		<0.0001		<0.0001		<0.0001
	Agricultural workers	6,867	6.81 (6.67, 6.95)		34.59 (31.99, 37.19)		20:59 (20:53, 21:05)		5:02 (4:57, 5:07)	
	Government/ public institution staff	24	6.79 (5.94, 7.64)		33.81 (27.88, 39.74)		21:37 (20:55, 22:19)		5:17 (4:28, 6:06)	
	Business/ service employee	339	6.73 (6.56, 6.90)		28.16 (22.63, 33.69)		21:24 (21:14, 21:34)		5:01 (4:51, 5:11)	

Continued

Age groups (years)	Characteristics	Total	Sleep duration $\bar{x}$ (hours) (95% *CI*)	*P*	Sleep latency $\bar{x}$ (min) (95% *CI*)	*P*	Bedtime $\bar{x}$ (95% *CI*)	*P*	Wake-up time $\bar{x}$ (95% *CI*)	*P*
	Teaching staff	28	7.52 (7.01, 8.03)		19.25 (16.05, 22.45)		21:24 (21:08, 21:40)		5:31 (5:21, 5:41)	
	Medical/health personnel	20	6.67 (6.01, 7.33)		20.77 (15.50, 26.04)		21:43 (21:20, 22:06)		5:12 (4:36, 5:48)	
	Students	–	–		–		–		–	
	Unemployed	2,168	6.88 (6.73, 7.03)		40.07 (36.77, 43.37)		21:00 (20:48, 21:12)		5:14 (5:05, 5:23)	
	Retired	3,252	6.70 (6.56, 6.84)		31.77 (28.90, 34.64)		21:33 (21:20, 21:46)		5:22 (5:10, 5:34)	
	Others	1,710	6.79 (6.61, 6.97)		35.98 (32.13, 39.83)		21:09 (20:53, 21:25)		5:10 (5:00, 5:20)	
	Unknown	84	7.05 (6.42, 7.68)		28.33 (27.60, 29.06)		21:08 (20:46, 21:30)		5:20 (4:50, 5:50)	

Note: In the occupation category, "Others" refers to occupations not included in the specific categories listed, while "Unknown" indicates that the occupation information is unavailable or could not be determined, "–" denotes not applicable for this age group.
Abbreviation: *CI*=confidence interval.

Among adolescents aged 15–17, rural residents slept significantly longer than their urban peers, a difference likely attributable to lower academic pressure, fewer extracurricular commitments, and reduced social demands in rural environments. Across other age groups, urban–rural disparities manifested primarily in sleep timing rather than duration: rural populations consistently retired earlier, a pattern that probably reflects the extended work hours and active nightlife characteristic of urban settings. Among highly educated individuals, later bedtimes coexisted with shorter sleep latency and longer total sleep duration — a pattern suggesting that greater health literacy and access to resources may enable more restorative sleep even within a compressed nocturnal window (*9*–*10*). Agricultural workers across all adult age groups maintained consistently early bedtimes, presumably in response to the demands of early morning labor schedules. Whether such early sleep timing confers benefits for overall sleep quality remains an important question for future investigation.

This study has several limitations. First, the cross-sectional design precludes causal inference. Second, reliance on self-reported sleep data introduces the potential for recall and social-desirability bias; future research would benefit from incorporating objective measures such as actigraphy. Third, because military personnel and institutionalized individuals were excluded from the sampling frame, the findings primarily generalize to the community-dwelling population. Fourth, certain occupational categories had relatively small sample sizes, which may yield unstable estimates and wider confidence intervals; findings for these categories should therefore be interpreted with caution. Finally, although the four selected sleep indicators provide valuable macroscopic insights into population-level sleep timing and quantity, they do not capture all dimensions of sleep health. Future studies should employ comprehensive, validated questionnaires or objective clinical measures — such as polysomnography — to enable a more thorough evaluation of sleep.

This study revealed substantial heterogeneity in sleep patterns among Chinese residents aged 15 years and above, with marked variation according to age, sex, geographic location, and socioeconomic status. Effective interventions must therefore adopt population-specific strategies rather than relying on universal guidelines. Policies should address the psychological burdens and work–life imbalances that contribute to prolonged sleep latency, particularly among women. Healthcare systems must also recognize how the convergence of occupational demands and menopausal transitions jointly undermine sleep in middle-aged women. Public health messaging should account for urban–rural disparities in sleep timing and lifestyle, promoting sleep hygiene practices that are compatible with occupational realities — including the early daily routines of agricultural workers. Ultimately, fostering sleep-conducive environments across diverse population segments requires tailored approaches that acknowledge the multifaceted determinants of sleep behavior.

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Preplanned Studies

Sleep Quality and the Influencing Factors in Older Adults Aged 65 Years and Above — 6 PLADs, China, 2025

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Summary

What is already known about this topic?

Sleep quality is a critical health determinant among older adults.

What is added by this report?

The prevalence of poor sleep quality among community-dwelling older adults aged 65 years and above was 48.39% [95% confidence interval (*CI*): 46.95%, 49.83%]. Sleep problems across all dimensions were more pronounced in females, rural residents, and individuals with depressive symptoms.

What are the implications for public health practice?

Sleep quality screening and intervention efforts should be strengthened, particularly for high-risk groups such as women, rural residents, and older adults with depression or chronic diseases.

ABSTRACT

Introduction: Sleep quality among older adults is an important determinant of overall health, yet research on this topic in China remains limited. This study presents the 2025 survey findings on sleep quality across various subgroups of older adults in China.

Methods: This study used data from the 2025 follow-up of the Healthy Aging and Elderly Longevity Survey (HAELS), covering six provincial-level administrative divisions (PLADs) in China. Subgroup differences were compared using chi-square tests, and multivariable logistic regression analysis was performed to identify factors associated with poor sleep quality.

Results: A total of 4,631 participants were included in the analysis. The overall prevalence of poor sleep quality was 48.39% [95% confidence interval (*CI*): 46.95%, 49.83%]. Independent risk factors included female sex [odds ratio (*OR*)=1.45, 95% *CI*: 1.26, 1.68], rural residence (*OR*=1.33, 95% *CI*: 1.16, 1.52), hypertension (*OR*=1.24, 95% *CI*: 1.10, 1.40), chronic digestive system diseases (*OR*=1.85, 95% *CI*: 1.55, 2.20), chronic urinary system diseases (*OR*=1.44, 95% *CI*: 1.19, 1.74), and depressive symptoms (*OR*=2.35, 95% *CI*: 2.03, 2.72) (all *P*<0.001). Among the multidimensional sleep problems, total sleep duration had the highest detection rate (41.44%, 95% *CI*: 40.01%, 42.87%), followed by sleep onset latency (35.95%, 95% *CI*: 34.57%, 37.35%) and sleep efficiency (30.79%, 95% *CI*: 29.46%, 32.14%).

Conclusion: Poor sleep quality is highly prevalent among older adults in China, with significant disparities across demographic and health subgroups. Strengthening sleep quality screening and intervention is essential, particularly for high-risk groups such as women, rural residents, and older adults with depression or chronic diseases.

Sleep quality, particularly among older adults, is a critical determinant of health and is associated with elevated risks of mortality, physical illness, and mental disorders (*1*). Given the rapid growth of the aging population, this issue poses a major public health challenge. A recent meta-analysis estimated the overall pooled prevalence of poor sleep quality among older adults at 50% [95% confidence interval (*CI*): 45%, 55%] (*2*). In recent years, research on sleep quality among older adults in China has been limited, focusing primarily on localized regions or clinical samples. This study presents the 2025 follow-up findings of the Healthy Aging and Elderly Longevity Survey (HAELS) on sleep quality across different subgroups of older adults in six provincial-level administrative divisions (PLADs) in China.

This study used data from the third round of the HAELS, which was initiated in 2019 across 6 PLADs (Beijing, Shandong, Jilin, Jiangxi, Ningxia, and Guangxi) to evaluate trends in healthy aging among community-dwelling older adults aged 65 years and above (*3*). These 6 PLADs were selected based on their level of economic development. From each province or municipality, two counties or urban districts were

randomly chosen. Within each county or urban district, two towns or subdistricts were selected using a multistage stratified probability-proportional-to-size (PPS) sampling approach. Two villages or communities were then chosen from each town or subdistrict, again employing PPS sampling. In the final stage, 100 participants were randomly drawn from residents aged 65 and above within each selected village or community. Overall, the HAELS recruited 4,800 participants, yielding a final sample of 4,690 in 2019 (*3*). Two rounds of follow-up were conducted in 2022 and 2025. In the 2025 round, to account for mortality, loss to follow-up, and shifts in age structure, additional subjects were recruited alongside continued tracking of the original cohort. This ensured that at least 100 surviving participants were surveyed in each village or community and that adults aged 65–70 years constituted at least 50% of the newly added subjects. In total, 4,775 eligible participants were enrolled, including 1,805 newly added subjects (37.8%), and 4,769 completed the survey. After excluding cases with missing sleep data, the final analytic sample comprised 4,631 participants (97.0%).

Sleep quality was assessed using the Pittsburgh Sleep Quality Index (PSQI), a validated self-report instrument (*4*). The questionnaire comprises 19 items grouped into seven domains: subjective sleep quality, sleep onset latency, total sleep duration, sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. Each domain is scored from 0 to 3, yielding a global PSQI score ranging from 0 to 21, with higher scores reflecting poorer sleep quality and greater severity of sleep-related problems. In this study, a score of ≥2 on any PSQI dimension was considered indicative of a problem in that dimension, and a total PSQI score >5 was classified as poor sleep quality. At this cutoff, the diagnostic sensitivity was 89.6% and the specificity was 86.5% (*4*). Demographic and health-related variables included age, sex, household registration, education level, hypertension, diabetes, chronic obstructive pulmonary disease (COPD), chronic digestive system diseases, chronic urinary system diseases, current smoking, alcohol consumption, physical activity, and depressive symptoms. Depression was assessed using the 15-item Geriatric Depression Scale (GDS-15), with scores ≥5 indicating depression.

Continuous variables were reported as means standard deviation (SD), and categorical variables as percentages with 95% *CI*s. The prevalence of overall PSQI scores and individual dimensions among older adults was presented as point estimates with 95% *CI*s. Subgroup differences were assessed using χ^2 tests, and multivariable logistic regression analysis was performed to identify factors associated with poor sleep quality. Radar charts were used to illustrate the multidimensional characteristics of sleep quality across age,sex, urban–rural residence, and depression status. All statistical analyses were conducted using R software (version 3.62, R Project for Statistical Computing, Vienna, Austria). Tests were two-tailed, with statistical significance defined as $P<0.05$.

Among the 4,631 older adults included in the analysis, the mean age was 74.3 years, with males accounting for 42.13% and urban residents for 33.56%. Table 1 presents the characteristics of participants stratified by sleep quality. The overall prevalence of poor sleep quality was 48.39% (95% *CI*: 46.95%, 49.83%), with higher rates observed among participants who were older, female, residing in rural areas, had lower educational attainment, had comorbid chronic diseases (hypertension, COPD, chronic digestive system diseases, and chronic urinary system diseases), or had depressive symptoms ($P<0.05$). Notably, among older adults with chronic digestive system diseases and those with depressive symptoms, the prevalence of poor sleep quality reached 64.49% (95% *CI*: 60.86%, 67.97%) and 65.90% (95% *CI*: 63.10%, 68.60%), respectively. Multivariable logistic regression analysis (Table 2) revealed that female sex (*OR*=1.45, 95% *CI*: 1.26, 1.68), rural residence (*OR*=1.33, 95% *CI*: 1.16, 1.52), hypertension (*OR*=1.24, 95% *CI*: 1.10, 1.40), chronic digestive system diseases (*OR*=1.85, 95% *CI*: 1.55, 2.20), chronic urinary system diseases (*OR*=1.44, 95% *CI*: 1.19, 1.74), and depressive symptoms (*OR*=2.35, 95% *CI*: 2.03, 2.72) were independent risk factors for poor sleep quality (all $P<0.001$). Conversely, middle school education (*vs.* primary school or below) and low physical activity (<150 min/week) were associated with better sleep quality.

Table 3 presents the detection rates of sleep problems across different PSQI dimensions among older adults. The highest detection rate was observed for total sleep duration at 41.44% (95% *CI*: 40.01%, 42.87%), followed by sleep onset latency at 35.95% (95% *CI*: 34.57%, 37.35%) and sleep efficiency at 30.79% (95% *CI*: 29.46%, 32.14%). The lowest detection rate was for use of sleep medication at 3.89% (95% *CI*: 3.35%, 4.48%).

Figure 1 displays the detection rates of sleep problems across various dimensions by subgroup.

TABLE 1. Characteristics of participants and prevalence of poor sleep quality among older adults from 6 PLADs of China, 2025.

Subgroup	*N*	Poor sleep quality % (95% *CI*)	χ^2	*P*
Age, years			7.609	0.022
65–74	2,628	46.88 (44.98, 48.79)		
75–84	1,754	49.77 (47.44, 52.11)		
≥85	249	54.62 (48.41, 60.69)		
Sex			55.071	<0.001
Male	1,951	41.98 (39.78, 44.21)		
Female	2,680	53.06 (51.15, 54.96)		
Residence			43.985	<0.001
Urban	1,554	41.51 (39.05, 44.01)		
Rural	3,077	51.87 (50.09, 53.65)		
Education level*			53.395	<0.001
Primary school or below	2,950	52.44 (50.62, 54.26)		
Middle school	1,105	41.45 (38.53, 44.42)		
High school or above	576	40.97 (36.94, 45.12)		
Hypertension			21.308	<0.001
Yes	2,447	51.61 (49.61, 53.61)		
No	2,184	44.78 (42.68, 46.9)		
Diabetes			0.445	0.505
Yes	859	49.48 (46.08, 52.87)		
No	3,772	48.14 (46.54, 49.75)		
COPD			12.15	0.001
Yes	342	57.60 (52.16, 62.87)		
No	4,289	47.66 (46.15, 49.16)		
Chronic digestive system diseases			87.898	<0.001
Yes	721	64.49 (60.86, 67.97)		
No	3,910	45.42 (43.85, 47.00)		
Chronic urinary system diseases			33.201	<0.001
Yes	595	59.50 (55.42, 63.45)		
No	4,036	46.75 (45.21, 48.31)		
Current smoking			23.692	<0.001
Yes	749	40.19 (36.67, 43.81)		
No	3,882	49.97 (48.39, 51.56)		
Drinking			18.081	<0.001
Yes	557	39.86 (35.79, 44.07)		
No	4,074	49.56 (48.01, 51.11)		
Physical activity per week*			2.521	0.284
<150 min	1,666	46.94 (44.52, 49.37)		
150–600 min	1,525	49.70 (47.17, 52.24)		
≥600 min	1,439	48.71 (46.10, 51.33)		
Depression symptom*			191.919	<0.001
No	3,423	42.42 (40.76, 44.10)		
Yes	1,173	65.90 (63.10, 68.60)		
Total	4,631	48.39 (46.95, 49.83)		

Abbreviation: PLADs=provincial-level administrative divisions; *CI*=confidence interval; COPD=chronic obstructive pulmonary disease.
* 1 case of physical activity information is missing, and 35 cases of depression information are missing.

TABLE 2. Multivariable logistic regression analysis of poor sleep quality in older adults from 6 PLADs of China, 2025.

Subgroup	*OR* (95% *CI*)	*P*
Age, years		
65–74	1	
75–84	1.04 (0.91, 1.18)	0.573
≥85	1.19 (0.90, 1.58)	0.214
Sex		
Male	1	
Female	1.45 (1.26, 1.68)	<0.001
Residence		
Urban	1	
Rural	1.33 (1.16, 1.52)	<0.001
Education level*		
Primary school or below	1	
Middle school	0.83 (0.71, 0.96)	0.015
High school or above	0.87 (0.71, 1.07)	0.181
Hypertension		
No	1	
Yes	1.24 (1.10, 1.40)	<0.001
Diabetes		
No	1	
Yes	0.98 (0.83, 1.15)	0.783
COPD		
No	1	
Yes	1.33 (1.05, 1.69)	0.020
Chronic digestive system diseases		
No	1	
Yes	1.85(1.55, 2.20)	<0.001
Chronic urinary system diseases		
No	1	
Yes	1.44 (1.19, 1.74)	<0.001
Current smoking		
Yes	1	
No	1.14 (0.95, 1.38)	0.159
Drinking		
Yes	1	
No	1.02 (0.83, 1.25)	0.880
Physical activity per week		
150–600 min	1	
<150 min	0.79 (0.68, 0.92)	0.002
≥600 min	0.94 (0.81, 1.09)	0.407
Depression symptom*		
No	1	
Yes	2.35 (2.03, 2.72)	<0.001

Abbreviation: PLADs=provincial-level administrative divisions; *OR*=odds ratio; *CI*=confidence interval; COPD=chronic obstructive pulmonary disease.

* 1 case of physical activity information is missing, and 35 cases of depression information are missing.

TABLE 3. Prevalence of multidimensions problem of the PSQI among older adults from 6 PLADs of China, 2025.

Dimension	Mean score (*SD*)	Sleep problem % (95% *CI*)
Subjective sleep quality	1.03 (0.76)	23.62 (22.41, 24.87)
Sleep onset latency	1.29 (1.03)	35.95 (34.57, 37.35)
Total sleep duration	1.15 (0.96)	41.44 (40.01, 42.87)
Sleep efficiency	0.85 (1.14)	30.79 (29.46, 32.14)
Sleep disturbances	1.06 (0.53)	15.78 (14.75, 16.87)
Use of sleep medication	0.12 (0.54)	3.89 (3.35, 4.48)
Daytime dysfunction	0.73 (0.90)	18.57 (17.46, 19.72)

Note: A score of ≥2 in any PSQI dimension indicates a problem in that dimension.
Abbreviation: PLADs=provincial-level administrative divisions; *CI*=confidence interval. *SD*=standard deviation.

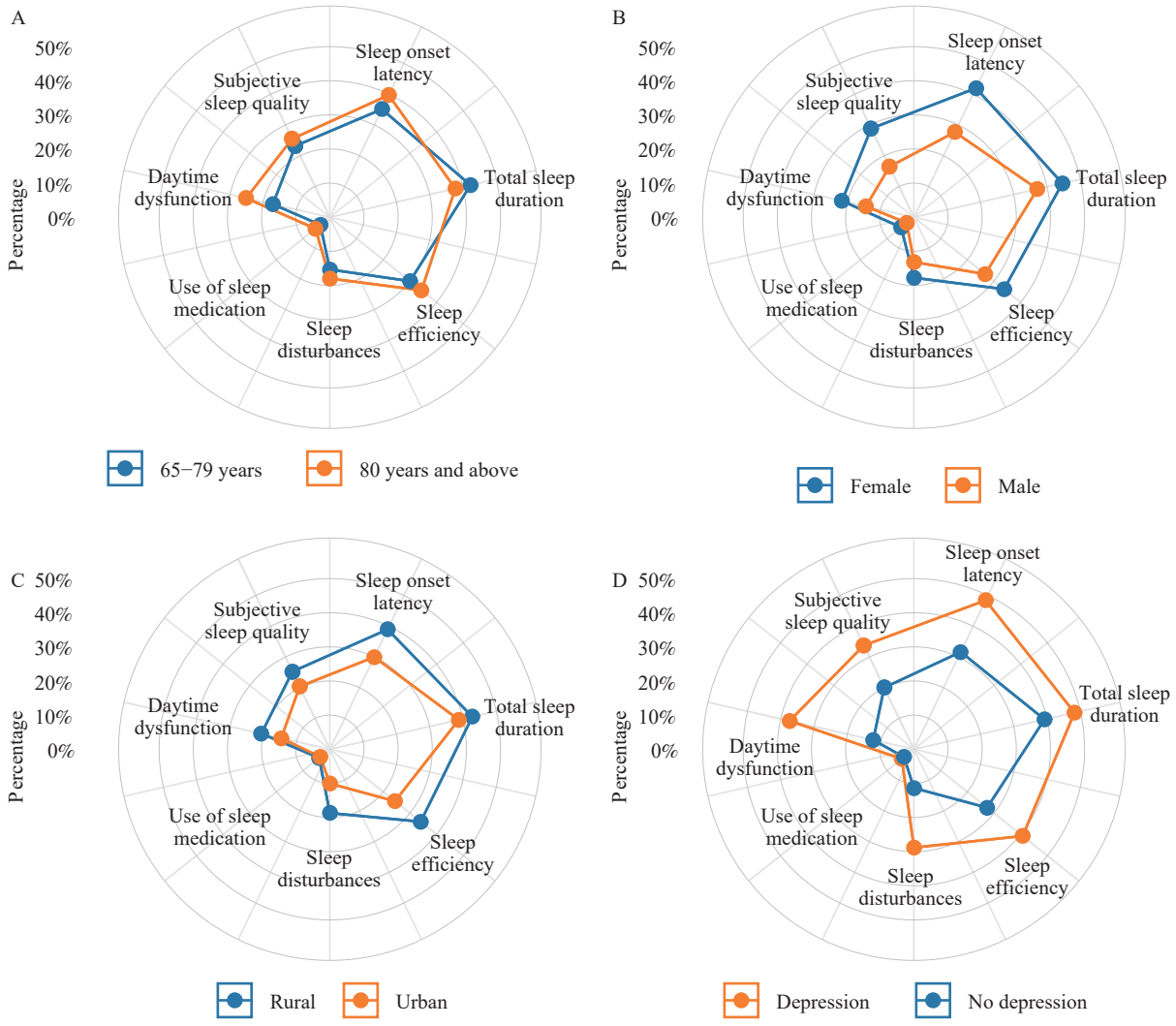

FIGURE 1. Radar chart of multidimensional PSQI assessment. (A) by age; (B) by sex; (C) by residence; (D) by depression status.
Abbreviation: PSQI=Pittsburgh Sleep Quality Index.

Across age, sex, urban–rural residence, and depression status, detection rates for each sleep dimension were consistently higher among females than males, higher in rural than urban areas, and higher among individuals with depressive symptoms than those without. With the exception of total sleep duration,

detection rates for all other sleep problems were higher among adults aged 80 years and above compared with those aged 65–79 years.

DISCUSSION

Sleep disturbances represent a prevalent and multifaceted health concern among older adults, profoundly affecting their overall well-being and daily functioning. Against this backdrop, the present study offers a comprehensive analysis of sleep quality among older adults using validated multidimensional assessments, describing the prevalence and distribution of sleep impairments across subpopulations defined by demographic and health-related characteristics. Our findings revealed that the prevalence of poor sleep quality among older adults was 48.39% (95% *CI*: 46.95%, 49.83%), consistent with the estimated global prevalence of 50.0% (*2*) and substantially higher than the rate of 28.2% reported in younger Chinese populations (*5*). These results underscore the need to integrate sleep problem screening and assessment into national basic public health services and the comprehensive geriatric evaluations conducted by medical institutions, thereby enabling earlier identification and more effective health management.

This study observed marked disparities in sleep quality among subgroups, with particularly poorer outcomes among the oldest-old adults, rural residents, and those with lower educational attainment. These populations may have lower health literacy, fewer adaptive coping strategies, and more limited access to healthcare resources, thereby perpetuating maladaptive sleep hygiene practices and dysfunctional beliefs about sleep (*6*). Female sex was identified as an independent risk factor for poor sleep quality (*OR*=1.45, 95% *CI*: 1.26, 1.68), a finding consistent with survey data from Shanghai (*7*). Sleep problems in women may be influenced by both biological and psychosocial factors (*8*). This study also found that chronic comorbidities — including hypertension, COPD, digestive disorders, and urinary diseases — as well as depressive symptoms adversely affected sleep quality. When developing sleep health promotion plans, particular attention should be directed toward women, rural residents, and populations at high risk for depression. Efforts should focus on disseminating sleep hygiene knowledge, expanding screening programs, improving healthcare accessibility, providing psychosocial support, and actively preventing and managing chronic diseases to improve sleep quality and overall health. Physical activity is widely recognized as an effective strategy for promoting sleep. However, this study found no evidence that engaging in ≥150 minutes of moderate-to-vigorous physical activity per week conferred better sleep quality compared with being insufficiently active. A meta-analysis demonstrated that moderate-intensity physical activity positively affected sleep quality, whereas high-intensity activity had no significant effect (*9*). Further research is needed to clarify the types and parameters of exercise that benefit sleep among older adults, including duration, intensity, optimal timing, and other relevant factors.

Analysis of individual sleep dimensions revealed that the most common problems involved total sleep duration, sleep onset latency, and sleep efficiency. These patterns were consistent across subgroups, with more pronounced impairments among women, rural residents, and individuals with depression. Additionally, adults aged 80 years and above and those with depressive symptoms experienced greater daytime dysfunction. A study conducted in Shandong found that poor subjective sleep quality, prolonged sleep onset latency, reduced sleep efficiency, sleep disturbances, daytime dysfunction, and the use of hypnotic medications were all associated with depressive symptoms in older adults (*10*). These findings highlight the multidimensional and population-specific nature of sleep problems, which may share a close bidirectional relationship with mental health — particularly depression. Future research should further explore the mechanisms linking various sleep dimensions to physiological and psychological outcomes, thereby providing evidence for the development of targeted intervention strategies.

This study has several limitations. First, the cross-sectional design precludes causal inference regarding the relationship between sleep quality and other factors. Second, the questionnaire-based approach may be subject to recall bias and influenced by subjective reporting. Third, this study did not incorporate objective sleep monitoring measures or additional biological data. Finally, the generalizability of the findings is constrained by the recruitment of participants from only 6 PLADs in China.

In summary, this study highlights the widespread problem of poor sleep quality among older adults and identifies significant associated risk factors, underscoring the need for individualized intervention strategies. These findings provide valuable insights for enhancing quality of life and health management in the aging population. Going forward, strengthening

sleep screening, evaluation, and targeted intervention for relevant risk factors will be essential to improving the effectiveness of comprehensive geriatric health management.

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Preplanned Studies

Stage-Specific Lifestyle Effects on the Dynamic Transitions of Metabolic Multimorbidity — Jiangsu Province, China, 2019–2024

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Summary

What is already known about this topic?

The prevalence of metabolic multimorbidity is rising in China and has been linked to lifestyle factors; however, evidence characterizing the dynamic transitions across disease states and the stage-specific influence of lifestyle behaviors remains scarce.

What is added by this report?

At baseline, the prevalence of metabolic multimorbidity was 24.14%, with males, older adults, and individuals with adverse lifestyle behaviors bearing a disproportionately elevated risk. Hepatic steatosis was associated with a markedly increased risk of progression to multimorbidity, while smoking, high-salt diets, and irregular physical activity each showed differential associations with specific disease transition pathways.

What are the implications for public health practice?

Lifestyle behaviors exert meaningful influence at every stage of metabolic disease progression, identifying them as priority targets for stage-specific prevention and control strategies in China.

ABSTRACT

Introduction: Metabolic multimorbidity is rising sharply in China and is closely linked to modifiable lifestyle behaviors; however, the dynamic transitions between metabolic disease states and the stage-specific effects of lifestyle factors on those transitions remain poorly understood.

Methods: We enrolled 9,673 participants from the Health Omics Preventive Examination Program (April 2019 – December 2024), each with at least two follow-up visits (median follow-up: 3.07 years; interquartile range: 1.09 years). A Markov multi-state model was used to evaluate the effects of eight lifestyle factors — smoking, alcohol consumption, physical activity, sleep duration, dietary oil intake, taste preference, and two dietary pattern scores — on transitions between disease states.

Results: At baseline, multimorbidity prevalence was 24.14%, with a substantially higher rate in males (40.92%) than in females (9.70%; $P<0.05$). Among single-disease conditions, hepatic steatosis conferred the greatest risk of progressing to multimorbidity. Lifestyle effects were markedly stage-specific: smoking [hazard ratio (HR)=2.44, 95% confidence interval (*CI*): 1.63, 3.65] and a high-salt diet (HR=2.28, 95% *CI*: 1.46, 3.55) significantly accelerated multimorbidity progression, whereas regular physical activity (HR=0.58, 95% *CI*: 0.40, 0.84) substantially reduced the risk of transitioning from single-disease to multimorbidity. These associations varied meaningfully by age and sex.

Conclusion: Lifestyle behaviors exhibit stage-specific associations with metabolic disease transitions, with the magnitude and direction of these effects differing by sex and age. These findings underscore the critical importance of implementing early, targeted, stage-specific lifestyle interventions to curb the growing burden of metabolic multimorbidity in China.

Metabolic diseases (MD) — including type 2 diabetes (T2D) and hypertension — share common pathophysiological mechanisms (*1*). In China, the prevalence of MD has risen steadily and frequently progresses to metabolic multimorbidity (MM; the coexistence of two or more metabolic diseases) (*2*), a condition associated with substantially higher risks of impaired physical function, cardiovascular events, and all-cause mortality (*3*).

Because metabolic diseases are largely preventable, a substantial body of research has examined associations between modifiable lifestyle factors and disease incidence (*4*). Traditional analytical frameworks, however, have concentrated on the onset of individual

diseases, overlooking the dynamic "healthy–single disease–multimorbidity" trajectory and failing to distinguish the stage-specific effects of lifestyle factors across different phases of disease progression (*5*–*6*).

To address this gap, the present study applied a Markov multi-state model (MSM) to evaluate associations between eight lifestyle factors — smoking, alcohol consumption, physical activity, sleep duration, dietary oil intake, taste preference, and two dietary pattern scores — and both the incidence of five single metabolic diseases (SMD; hypertension, T2D, dyslipidemia, hepatic steatosis, and hyperuricemia) and the subsequent development of MM among Chinese adults. Obesity was excluded from the SMD framework because it frequently co-occurs with hepatic steatosis, which more accurately reflects central or visceral adiposity (*7*). By capturing the full disease progression continuum, this analysis aims to provide a comprehensive understanding of how lifestyle behaviors drive SMD onset and accelerate progression to MM, thereby informing chronic disease prevention strategies in the Chinese population.

This study drew on data from the Health Omics Preventive Examination (HOPE) Program (Supplementary Material, available at https://weekly.chinacdc.cn/), which enrolled 71,010 participants between April 2019 and December 2024 and collected baseline questionnaires alongside biospecimen data. Of these, 14,423 individuals had complete baseline disease data and at least two follow-up assessments. After further excluding those with missing data on more than 2 of the eight lifestyle factors, 9,673 participants remained in the final analytic sample.

Lifestyle factors were assessed via baseline self-reported questionnaires. The five metabolic diseases were identified using a combination of clinical indicators, symptoms, self-reports, and medication use (Supplementary Material). MM was defined as the concurrent presence of two or more of these metabolic diseases. The follow-up period extended from the baseline examination to either the first diagnosis of metabolic multimorbidity or censoring on December 31, 2024. MSM was then applied to evaluate the effects of each lifestyle factor on transitions between metabolic disease states. All statistical analyses were two-sided and conducted using R software (version 4.3.1, R Core Team, Vienna, Austria).

At baseline, the prevalence of T2D, hypertension, dyslipidemia, hyperuricemia, and hepatic steatosis stood at 2.23%, 13.45%, 22.85%, 21.00%, and 26.66%, respectively (Supplementary Figure S1, available at https://weekly.chinacdc.cn/). Males demonstrated significantly higher prevalence across all five metabolic conditions compared with females (P<0.05). Hepatic steatosis was the most prevalent condition among males (43.46%), whereas dyslipidemia predominated among females (13.87%). Age-stratified analyses revealed distinct distributional patterns: hyperuricemia was most frequent among participants under 35 years of age (22.73%), while hypertension was most common among those over 55 years (52.74%). The prevalence of all metabolic conditions rose progressively with advancing age (P<0.05). Overall multimorbidity (MM) prevalence at baseline was 24.14%, markedly higher in males (40.92%) than in females (9.70%; P<0.05). Hepatic steatosis–related combinations represented the most common MM patterns both overall and within sex-specific strata (Supplementary Figure S1).

Table 1 summarizes the baseline sociodemographic, lifestyle, and clinical characteristics of the study population, stratified by baseline disease status. The three groups differed significantly in age, sex, education level, and lifestyle behaviors (P<0.05). Both median age and the proportion of male participants increased progressively from the MD-free group through the SMD group to the MM group. Unhealthy lifestyle behaviors — including smoking, alcohol consumption, physical inactivity, high dietary oil intake, and a high-salt diet — followed the same ascending pattern across these groups.

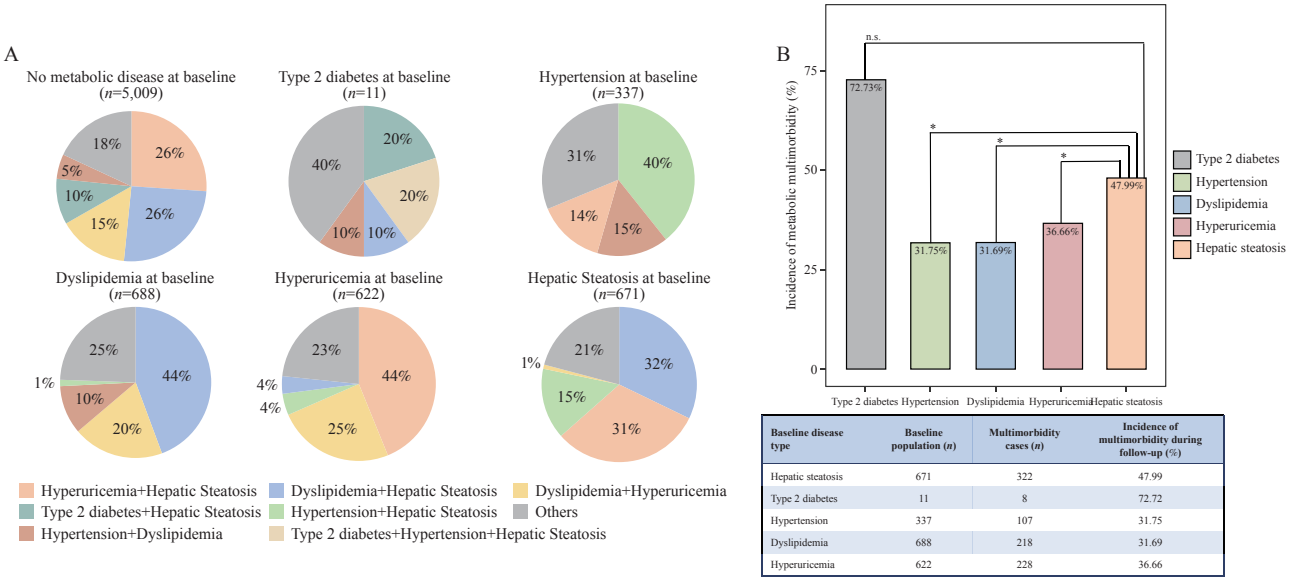
Over a median follow-up of 3.49 years [interquartile range (IQR): 2.25–5.12 years], 1,244 incident MM cases emerged, representing 16.95% of the study population. Males accounted for a disproportionate share, with 832 cases (31.47%) compared with 412 among females (8.78%; P<0.05), and incidence rose steadily with advancing age. Figure 1 illustrates the predominant patterns of incident MM, revealing that hepatic steatosis-related MM combinations ranked consistently as the most common, irrespective of participants' baseline disease status — whether MD-free or presenting with SMD. Among those with baseline hepatic steatosis, the MM incidence reached 47.99%, significantly exceeding rates associated with hypertension, dyslipidemia, or hyperuricemia (P<0.05). Although type 2 diabetes appeared to carry an even higher incidence, that estimate rested on a small sample and lacked statistical stability. Taken together, these findings position hepatic steatosis as a potentially pivotal driver in the development of MM.

To characterize disease progression, transitions

TABLE 1. Baseline characteristics of participants by metabolic disease status.

Baseline characteristics	Total *N*=9,673	No diseases *N*=5,009	Single disease *N*=2,329	Comorbidity *N*=2,335	*P*
Sociodemographic factors					
Age (years)	35.43 (30.43, 42.02)	34.14 (29.63, 39.73)	36.20 (30.68, 43.63)	38.35 (32.17, 49.00)	<0.05
Sex, *n* (%)					<0.05
Male	4,475 (46.26)	1,326 (26.47)	1,318 (56.59)	1,831 (78.42)	
Female	5,198 (53.74)	3,683 (73.53)	1,011 (43.41)	504 (21.58)	
Educational level, *n* (%)					<0.05
Below college	338 (3.49)	79 (1.58)	99 (4.25)	160 (6.86)	
College or above	9,333 (96.51)	4,929 (98.42)	2,230 (95.75)	2,174 (93.14)	
Lifestyle behavior factors					
Smoking status, *n* (%)					<0.05
Never smoking	8,346 (86.50)	4,712 (94.24)	1,959 (84.37)	1,675 (72.01)	
<20 pack-years	1,089 (11.29)	260 (5.20)	329 (14.17)	500 (21.50)	
≥20 pack-years	213 (2.21)	28 (0.56)	34 (1.46)	151 (6.49)	
Alcohol consumption, *n* (%)					<0.05
Never drinking	8,339 (86.37)	4,610 (92.22)	1,952 (84.03)	1,777 (76.17)	
Moderate drinking (men <60 g/day, women <50 g/day)	1,289 (13.35)	385 (7.70)	365 (15.71)	539 (23.10)	
Heavy drinking (men ≥60 g/day, women ≥50 g/day)	27 (0.28)	4 (0.08)	6 (0.26)	17 (0.73)	
Regular physical activity, *n* (%)					<0.05
No	6,155 (63.68)	3,329 (66.54)	1,372 (58.93)	1,454 (62.30)	
Yes	3,510 (36.32)	1,674 (33.46)	956 (41.07)	880 (37.70)	
Sleep duration, Median (IQR)	7.00 (7.00,8.00)	7.00 (7.00,8.00)	7.00 (6.50,8.00)	7.00 (6.50,8.00)	<0.05
Cooking oil consumption, *n* (%)					<0.05
Low	2,382 (24.63)	1,298 (25.92)	625 (26.84)	459 (19.66)	
Moderate	6,326 (65.41)	3,275 (65.40)	1,469 (63.07)	1,582 (67.75)	
High	964 (9.96)	435 (8.68)	235 (10.09)	294 (12.59)	
Dietary taste preference, *n* (%)					<0.05
Light	2,701 (27.93)	1,489 (29.73)	681 (29.25)	531 (22.74)	
Moderate	5,885 (60.85)	3,057 (61.04)	1,404 (60.31)	1,424 (60.99)	
Salty	1,085 (11.22)	462 (9.23)	243 (10.44)	380 (16.27)	
Healthy dietary pattern score, Median (IQR)	0.06 (−0.57, 0.63)	0.10 (−0.5, 0.65)	0.08 (−0.55, 0.69)	−0.05 (−0.74, 0.51)	<0.05
High-calorie dietary pattern score, Median (IQR)	−0.16 (−0.78, 0.60)	−0.15 (−0.77, 0.58)	−0.22 (−0.81, 0.61)	−0.12 (−0.75, 0.64)	0.15
Clinical measurements					
SBP (mmHg), Median (IQR)	118.00 (109.00, 129.00)	113.00 (106.00, 122.00)	121.00 (112.00, 131.00)	130.00 (119.00, 140.00)	<0.05
DBP (mmHg), Median (IQR)	74.00 (67.00, 81.00)	70.00 (65.00, 76.00)	75.00 (68.00, 82.00)	81.00 (74.00, 88.00)	<0.05
FPG (mmol/L), Median (IQR)	4.96 (4.67, 5.27)	4.87 (4.61, 5.15)	4.98 (4.69, 5.28)	5.18 (4.86, 5.64)	<0.05
HbAc1 (%), Median (IQR)	5.30 (5.10, 5.50)	5.21 (5.07, 5.40)	5.30 (5.10, 5.50)	5.44 (5.21, 5.70)	<0.05
TC (mmol/L), Median (IQR)	4.86 (4.29, 5.48)	4.69 (4.18, 5.21)	5.02 (4.38, 5.74)	5.14 (4.48, 5.93)	<0.05
TG (mmol/L), Median (IQR)	1.09 (0.79, 1.58)	0.88 (0.70, 1.15)	1.20 (0.89, 1.61)	1.89 (1.33, 2.65)	<0.05
HDL-C (mmol/L), Median (IQR)	1.34 (1.15, 1.56)	1.45 (1.28, 1.65)	1.30 (1.13, 1.53)	1.13 (0.99, 1.31)	<0.05
LDL-C (mmol/L), Median (IQR)	2.93 (2.51, 3.39)	2.76 (2.40, 3.14)	3.10 (2.63, 3.61)	3.22 (2.76, 3.76)	<0.05
SUA (μmol/L), Median (IQR)	322.00 (267.00, 394.00)	283.00 (244.00, 326.00)	355.00 (295.30, 406.00)	424.00 (364.00, 473.00)	<0.05
Prevalence of hepatic steatosis, *n* (%)	2,577 (26.64)	–	671 (28.81)	1,906 (81.63)	<0.05

Note: Continuous variables are presented as median (IQR), and categorical variables as number (percentage). Differences among groups were assessed using the Kruskal–Wallis test for continuous variables and the chi-square (χ^2) test for categorical variables.
Abbreviation: SBP=systolic blood pressure; DBP=diastolic blood pressure; FPG=fasting plasma glucose; HbA1c=glycated hemoglobin; TC=total cholesterol; TG=triglycerides; HDL-C=high-density lipoprotein cholesterol; LDL-C=low-density lipoprotein cholesterol; SUA= serum uric acid; IQR=interquartile range.



Baseline disease type	Baseline population (*n*)	Multimorbidity cases (*n*)	Incidence of multimorbidity during follow-up (%)
Hepatic steatosis	671	322	47.99
Type 2 diabetes	11	8	72.72
Hypertension	337	107	31.75
Dyslipidemia	688	218	31.69
Hyperuricemia	622	228	36.66

FIGURE 1. Patterns and comparisons of metabolic multimorbidity during follow-up. (A) Key metabolic multimorbidity patterns during follow-up by baseline metabolic disease status. (B) Incidence of metabolic multimorbidity by baseline single metabolic disease type.
Note: In panel A, comorbidity combinations were first identified within each baseline disease group, and the most frequent patterns were consolidated into a unified set of seven combinations displayed across all pie charts. Less frequent combinations are grouped as "Others".

across three states — MD-free, SMD, and MM — were tracked in 7,338 participants who were free of MM at baseline. The incidence rates for the MD-free–to–SMD and SMD-to–MM transitions were 97.27 and 137.03 per 1,000 person-years, respectively (Supplementary Figure S2, available at https://weekly.chinacdc.cn/). Recognizing well-established sex- and age-related differences in lifestyle behaviors and metabolic multimorbidity, we conducted sex- and age-stratified multi-state models (Figure 2 and Supplementary Table S1, available at https://weekly.chinacdc.cn/). In males, both smoking [hazard ratio (HR)=2.44, 95% confidence interval (*CI*): 1.63, 3.65] and a high-salt diet (HR=2.28, 95% *CI*: 1.46, 3.55) significantly elevated the risk of progressing directly from MD-free to MM. Among females, a high-oil diet showed a nominally significant association with increased MM risk (HR=1.76, 95% *CI*: 1.05, 2.96); conversely, regular physical activity (HR=0.58, 95% *CI*: 0.40, 0.84) and healthy dietary patterns (HR=0.83, 95% *CI*: 0.71, 0.98) were each nominally associated with a reduced risk of progression from SMD to MM. Age-stratified analyses revealed that among participants younger than 40 years, smoking (HR=2.04, 95% *CI*: 1.27, 3.30) and a high-salt diet (HR=1.74, 95% *CI*: 1.08, 2.80) accelerated the MD-free–to–MM transition, while regular physical activity offered nominal protection against SMD-to-MM progression (HR=0.77, 95% *CI*: 0.61, 0.97). In participants aged 40 years or older, the hazard estimates for both smoking (HR=3.16, 95% *CI*: 1.52, 6.55) and a high-salt diet (HR=2.27, 95% *CI*: 1.18, 4.36) were markedly stronger than those observed in the younger stratum. Additionally, alcohol consumption (HR=1.89, 95% *CI*: 1.29, 2.78) independently heightened the risk of SMD onset in this older group, and a high-oil diet (HR=1.78, 95% *CI*: 1.14, 2.77) further increased the likelihood of advancing from SMD to MM.

DISCUSSION

Drawing on data from the HOPE cohort, this study characterized metabolic comorbidity patterns in Chinese adults, mapped disease transitions across three states, and evaluated the influence of lifestyle behaviors on those transitions. At baseline, the prevalence of five MDs and MM was higher in males than in females, and the prevalence of each MD rose with age (P<0.05). Hepatic steatosis-related comorbidity patterns were the most prevalent in the study population. Notably, individuals with hepatic steatosis faced a substantially elevated risk of developing metabolic comorbidity — a finding consistent with prior evidence underscoring the

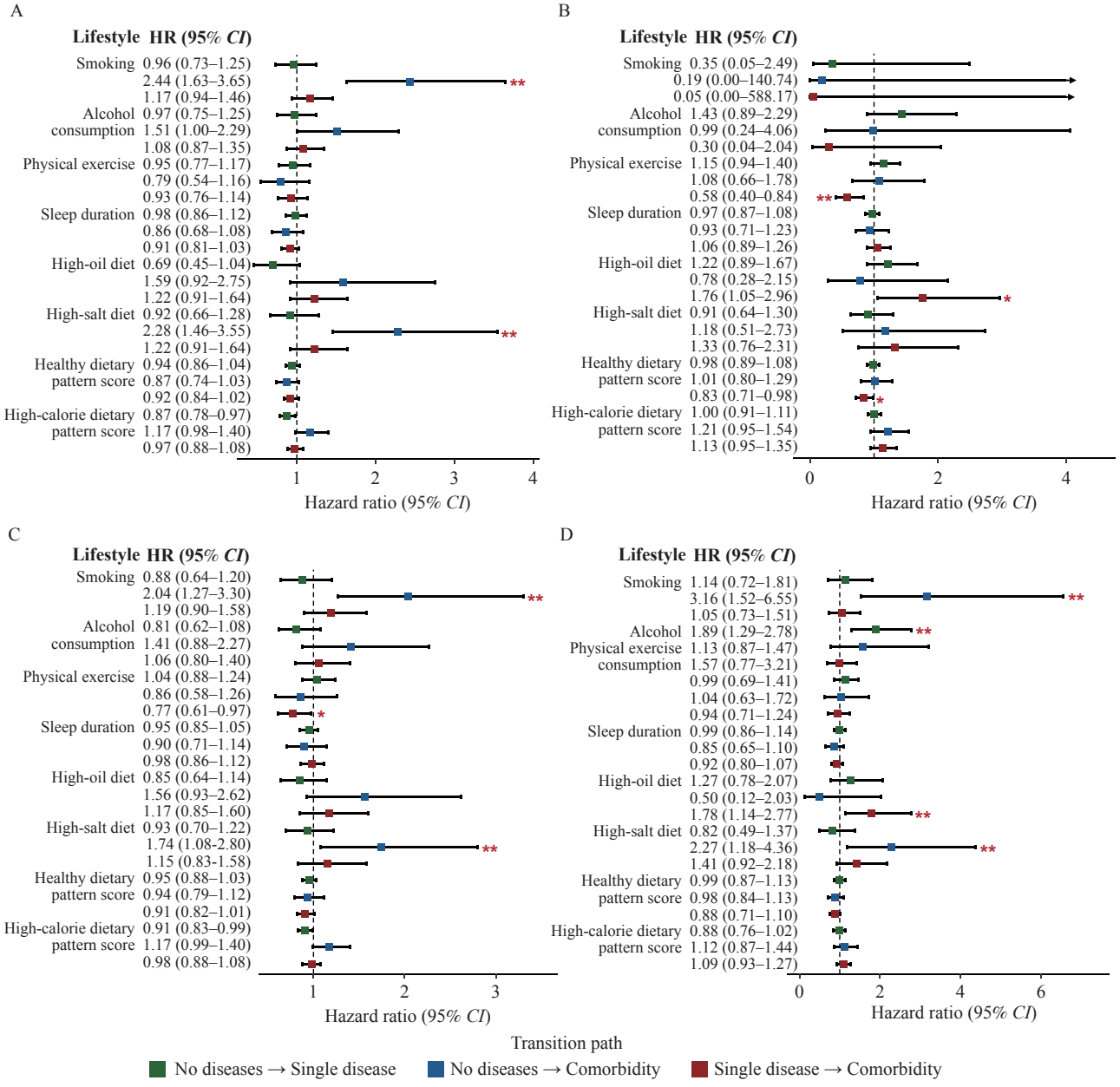


FIGURE 2. Effects of lifestyle factors on different disease transition pathways. (A) Males; (B) Females; (C) Age<40 years; (D) Age≥40 years.
Note: Forest plots present hazard ratios (HRs) and 95% confidence intervals (*CI*s) derived from multistate model analyses. Models were adjusted for education level and physical examination center.
Abbreviations: HR=hazard ratio; *CI*=confidence interval; No diseases=no metabolic diseases; Single disease=single metabolic disease; Comorbidity=metabolic multimorbidity.
* indicates *P*<0.05; ** indicates *P*_FDR<0.05.

central role of hepatic metabolic dysfunction in driving insulin resistance (*8*), which itself has been identified as a key pathological mechanism of metabolic syndrome (*9*). Taken together, these observations suggest that hepatic steatosis may serve as an early sentinel of metabolic disease progression and could help clinicians identify populations at heightened risk of metabolic multimorbidity before it fully develops.

Sex-specific differences in the associations between lifestyle factors and metabolic multimorbidity progression likely reflect, at least in part, genuine differences in lifestyle behaviors between men and women. Among the present findings, smoking was strongly associated with a higher risk of progression from SMD to MM in males, yet no comparable association emerged in females — an asymmetry

almost certainly attributable to the stark disparity in smoking prevalence between the two groups (24.32% in males versus 0.51% in females).

Prior research has demonstrated that lifestyle interventions combining healthy dietary patterns with regular moderate-intensity physical activity can reduce the prevalence of metabolic syndrome (*10*). Those studies, however, focused on the onset of individual metabolic diseases and did not account for dynamic disease progression. To address this gap, the present study employed a multi-state model to examine disease transitions over time, revealing that progression was not strictly unidirectional and, importantly, that stage-specific intervention opportunities exist. Regular physical activity and healthier dietary patterns were both associated with a lower risk of progression from SMD to MM among females, suggesting that interventions targeting these behaviors may be especially effective for women. Furthermore, a preference for high-salt diets was associated with an increased risk of progression from SMD to MM among males, and this association held consistently across both younger (<40 years) and older (≥40 years) age groups.

This study has several limitations that warrant acknowledgment. First, all lifestyle data were self-reported, introducing the potential for reporting bias. Second, restricting the analysis to participants with at least two follow-up visits may have introduced selection bias, although key baseline characteristics remained similar to those of the overall cohort. Residual confounding from unmeasured cardiometabolic family history cannot be fully excluded. Finally, the relatively short follow-up period may have constrained the observation of long-term disease trajectories and could have preferentially captured more rapid patterns of disease progression.

In sum, adopting healthier lifestyle behaviors holds meaningful potential for preventing or delaying the progression of metabolic multimorbidity. Individuals with hepatic steatosis, in particular, warrant prioritization for targeted lifestyle interventions — a finding that provides practical evidence for stage-specific prevention strategies in the broader effort to control metabolic disease.

Conflicts of interest: No conflicts of interest.

Ethical statement: The study protocol of the HOPE program was approved by the Institutional Review Board of Nanjing Medical University (Ref: 2023-278).

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SUPPLEMENTARY MATERIAL

The Health Omics Preventive Examination (HOPE) Program

The Health Omics Preventive Examination (HOPE) Program is a multicenter prospective cohort study conducted in Jiangsu Province, China, enrolling individuals who undergo routine health examinations (*1*). Between April 2019 and December 2024, 71,010 participants completed baseline questionnaires and provided biospecimen data. The Institutional Review Board of Nanjing Medical University approved the HOPE cohort study protocol (Ref: 2023-278), and all participants provided written informed consent. Of the 14,423 individuals with complete baseline disease data and at least two follow-up assessments, 9,673 met the inclusion criteria for analysis, each having no more than two missing values across the eight lifestyle factors examined.

Methods

Definitions of diseases. This study examined five metabolic diseases: hypertension, type 2 diabetes, dyslipidemia, hepatic steatosis, and hyperuricemia. Clinicians diagnosed each condition through a comprehensive assessment integrating metabolic indicators, clinical manifestations, self-reported medical history, and current medication use (*2*–*5*).

Hypertension: Defined as systolic blood pressure (SBP) ≥140 mmHg, diastolic blood pressure (DBP) ≥90 mmHg, and/or current use of antihypertensive medication;

Type 2 Diabetes: Defined as fasting plasma glucose (FPG) ≥7.0 mmol/L (126 mg/dL), glycated hemoglobin (HbA1c) ≥6.5%, 2-hour plasma glucose during an oral glucose tolerance test (OGTT-2h) ≥11.1 mmol/L (200 mg/dL), and/or current use of insulin or antidiabetic medication;

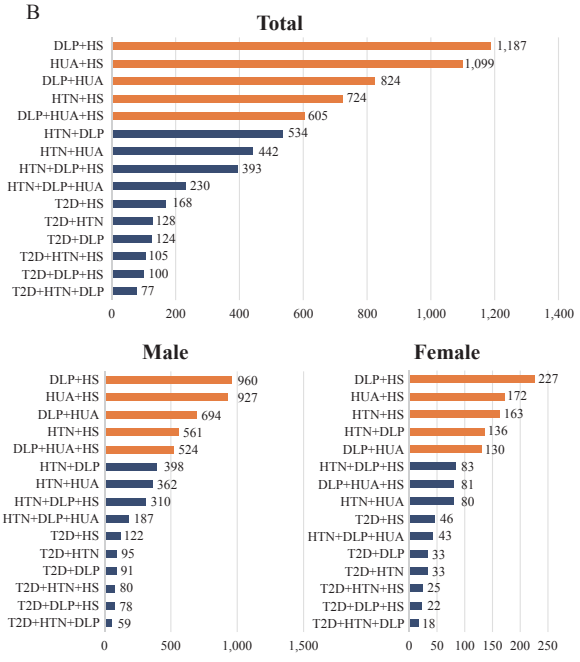
Dyslipidemia: Defined as total cholesterol (TC) ≥6.2 mmol/L, triglycerides (TG) ≥2.3 mmol/L, low-density lipoprotein cholesterol (LDL-C) ≥4.1 mmol/L, high-density lipoprotein cholesterol (HDL-C) <1.0 mmol/L, and/or current use of lipid-lowering medication;

A

	Total population	Stratified by sex		
		Male	Female	*P*
N	9,673	4,475	5,198	
Metabolic disease				
Type 2 diabetes	215 (2.23)	149 (3.33)	66 (1.27)	<0.05
Hypertension	1,298 (13.45)	901 (20.13)	397 (7.64)	<0.05
Dyslipidemia	2,207 (22.85)	1,486 (33.21)	721 (13.87)	<0.05
Hyperuricemia	2,028 (21.00)	1,589 (35.51)	439 (8.45)	<0.05
Hepatic steatosis	2,577 (26.66)	1,945 (43.46)	632 (12.16)	<0.05
Metabolic comorbidity	2,335 (24.14)	1,831 (40.92)	504 (9.70)	<0.05

	Stratified by age group				
	<35	(35,45]	(45,55]	>55	*P*
N	4,642	3,195	1,161	675	
Metabolic disease					
Type 2 diabetes	21 (0.45)	48 (1.50)	53 (4.57)	93 (13.78)	<0.05
Hypertension	294 (6.33)	357 (11.17)	291 (25.06)	356 (52.74)	<0.05
Dyslipidemia	816 (17.58)	736 (23.04)	354 (30.49)	301 (44.59)	<0.05
Hyperuricemia	1,055 (22.73)	607 (19.00)	219 (18.86)	147 (21.78)	<0.05
Hepatic steatosis	1,014 (21.84)	861 (26.95)	402 (34.63)	300 (44.44)	<0.05
Metabolic comorbidity	869 (18.72)	721 (22.57)	373 (32.13)	372 (55.11)	<0.05

B



SUPPLEMENTARY FIGURE S1. Baseline prevalence and comorbidity patterns of metabolic diseases by sex and age group. (A) Prevalence of metabolic diseases at baseline by sex and age group. (B) Baseline patterns of metabolic comorbidities in the overall population and by sex.

Note: Data are presented as number (percentage). Differences between sex and age groups were assessed using the chi-square (χ^2) test.

Abbreviation: HTN=Hypertension; T2D=Type 2 diabetes; DLP=Dyslipidemia; HS=Hepatic steatosis; HUA=Hyperuricemia.

Hyperuricemia: Defined as serum uric acid ≥420 μmol/L in men or ≥360 μmol/L in women, and/or current use of uric acid–lowering medication;

Hepatic steatosis: Diagnosed based on imaging findings from ultrasonography or computed tomography.

Definitions of Lifestyle Variables

Smoking status: Current or former smokers were defined as participants who currently smoke or previously smoked and have quit; never smokers were defined as participants who never smoked.

Alcohol consumption: Alcohol consumption was defined based on self-reported questionnaire data. Participants were classified as alcohol consumers if they reported drinking at least once per month or had a history of alcohol use; non-consumers were defined as those who reported never, rarely, or only occasional drinking on special occasions.

Regular physical activity: Participants reporting consistent exercise were classified as engaging in regular physical activity, whereas those reporting occasional or no exercise were classified as not regularly physically active.

Sleep duration: Participants self-reported the average number of hours they sleep per day (hours).

High-oil diet: Participants reporting "low" or "moderate" oil intake preference were classified as "non-high-oil diet"; those reporting "high" oil intake preference were classified as "high-oil diet".

High-salt diet: Participants reporting "light" or "moderate" salt intake preference were classified as "non-high-salt diet"; those reporting "salty" preference were classified as "high-salt diet".

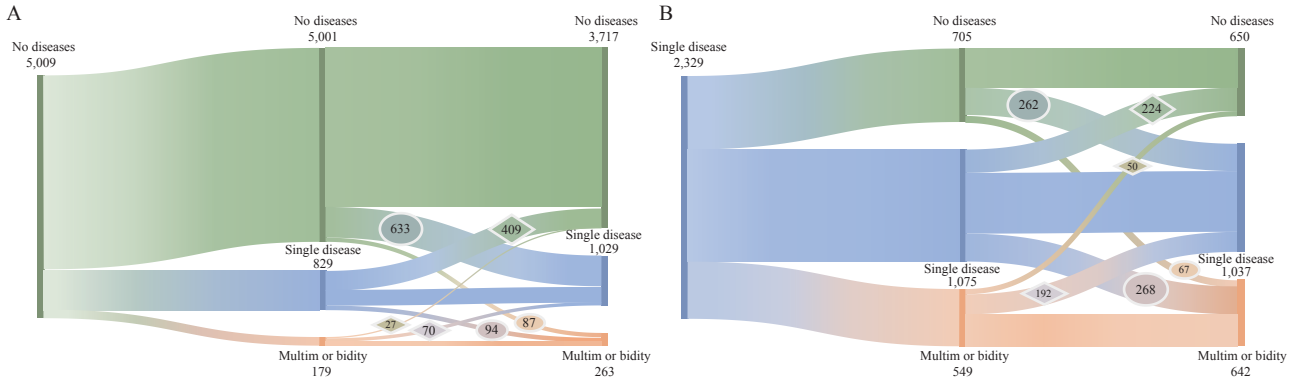
Definition of dietary pattern scores: Dietary patterns were derived from dietary questionnaire completed by participants at baseline. The questionnaire asked, "How often do you eat the following foods?" with seven response options: "Never or <1 time/month," "2–3 times/month," "1–2 times/week," "3–4 times/week," "5–6 times/week," "≥1 time/day," and "Prefer not to answer." A total of 20 food items were included in the dietary questionnaire, and each food item was assigned a frequency score ranging from 1 to 6 and treated as a continuous variable. Principal component analysis (PCA) was then conducted to identify the major dietary patterns in the study population. Two principal components were extracted:

Healthy dietary pattern: Characterized by high consumption of vegetables, fruits, whole grains, and soy products, representing a balanced and nutrient-rich diet;

High-calorie dietary pattern: Characterized by frequent consumption of fried foods, sweets, and sugar-sweetened beverages, representing a diet with higher energy density.

The two principal component scores (RC1 and RC2) derived from the PCA were standardized via z-transformation and subsequently used as individual-level dietary pattern scores in all downstream analyses.

Markov multi-state model. We employed a Markov multi-state model to evaluate the stage-specific associations



	Events (*n*)	Incidence rate (per 1,000 person-years)	Follow-up time (median)
No metabolic diseases→Single metabolic disease	1,029	97.27 (91.41–103.39)	2.00
No metabolic diseases→Metabolic multimorbidity	263	24.31 (21.46–27.44)	2.01
Single metabolic diseases →Metabolic multimorbidity	642	137.03 (126.64–148.05)	1.99

SUPPLEMENTARY FIGURE S2. Transitions of metabolic disease status during follow-up. (A) No metabolic diseases at baseline. (B) Single metabolic disease at baseline.

Note: The figure illustrates state transitions occurring during follow-up. Event counts, incidence rates (per 1,000 person-years), and median follow-up time are provided for each transition pathway.

between lifestyle factors and the dynamic progression of metabolic disease. This framework enables simultaneous estimation of transition risks across multiple stages: from a disease-free state to a single metabolic condition, and subsequently to metabolic multimorbidity. The model structure accommodates transitions between all disease states, encompassing forward progression, potential reverse transitions, and direct transitions that bypass intermediate states.

The model operates under the Markov assumption, which holds that future risk depends solely on the current disease state, independent of the time previously spent in earlier states (*6*). To quantify the influence of lifestyle factors on these dynamics, we modelled the transition intensity — defined as the instantaneous risk of moving from state r to state s at time t — using a proportional hazards specification (*7*–*8*):

$$q_{rs}(t|Z) = q_{rs,0}(t)\exp\left(\beta_{rs}^{T}Z\right)$$

where $q_{rs,0}(t)$ denotes the baseline hazard for the specific transition $r \to s$, Z denotes the vector of lifestyle factors, and β_{rs} is the corresponding vector of transition-specific regression coefficients.

SUPPLEMENTARY TABLE S1. Distribution of eight lifestyle factors by sex among study participants.

Lifestyle factors	Male	Female	*P*
	n=2,644	*n*=4,694	
Smoking status, *n* (%)			<0.05
Never smoking	2,001 (75.68)	4,670 (99.49)	
Current/former smoker	643 (24.32)	24 (0.51)	
Alcohol consumption, *n* (%)			<0.05
Never drinking	1,994 (75.44)	4,568 (97.32)	
Current/former/occasional drinker	649 (24.56)	126 (2.68)	
Physical exercise, *n* (%)			<0.05
No	1,425 (53.92)	3,276 (69.88)	
Yes	1,218 (46.08)	1,412 (30.12)	
Sleep duration, Median (IQR)	7.00 (7.00, 8.00)	7.00 (7.00, 8.00)	0.07
High-oil diet, *n* (%)			<0.05
No	2,368 (89.56)	4,299 (91.60)	
Yes	276 (10.44)	394 (8.40)	
High-salty diet, *n* (%)			<0.05
No	2,309 (87.36)	4,322 (92.09)	
Yes	334 (12.64)	371 (7.91)	
Healthy dietary pattern score, Median (IQR)	−0.01 (−0.63, 0.62)	0.14 (−0.46, 0.67)	<0.05
High-calorie dietary pattern score, Median (IQR)	−0.10 (−0.75,0.67)	−0.20 (−0.80,0.54)	<0.05

Note: Continuous variables are presented as median (IQR), and categorical variables as number (percentage). Differences among groups were assessed using the Kruskal–Wallis test for continuous variables and the chi-square (χ^2) test for categorical variables.
Abbreviation: IQR=interquartile range.

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Vital Surveillances

Temporal Trends and Characteristics of Immunization Consultation Hotline Calls — Suzhou City, Jiangsu Province, China, 2018–2024

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ABSTRACT

Introduction: Vaccination remains a topic of widespread public concern. To ensure that professionals could deliver accurate information to the public directly and efficiently, Suzhou established a dedicated immunization program consultation hotline in 2018. To date, comprehensive, long-term standardized statistical analyses of immunization consultation hotlines in China remain scarce. This study analyzes temporal trends, category characteristics, and shifts in core public concerns regarding immunization consultations in Suzhou from 2018 to 2024, offering evidence to support the optimization of local public health service allocation.

Methods: Dedicated professionals answered all calls in real time within a designated room (operating hours: 9:00–17:00), and the full content of each call was recorded. Natural language processing (NLP) was applied for text preprocessing, categorical feature definition, frequency counting, and systematic analysis using Microsoft Excel. Descriptive statistics were performed and figures were generated using Python 3.12.1.

Results: A total of 76,154 valid records were collected. Annual call volume peaked at 15,365 in 2021 before declining by 80% to 3,025 in 2024. Monthly call volumes were highest between May and September and lowest in January and February. The most common consultation category was assessment form-related inquiries (24,911; 32.71%), followed by vaccination services (15,387; 20.21%) and vaccination policies (15,026; 19.73%). The most frequently consulted vaccines were the human papillomavirus vaccine (HPV) and the rabies vaccine (RV).

Conclusions: The hotline served as a direct communication channel between the public and government, accurately reflecting dynamic shifts in public immunization demands while providing actionable support for immunization program. The evolving pattern of public vaccination concerns demonstrates measurable improvements in the quality and efficiency of immunization program in Suzhou.

As a cornerstone of public health, immunization enables people of all ages to live longer, healthier lives while alleviating the socioeconomic burden of infectious diseases worldwide (*1*–*3*). China formally launched the Expanded Program on Immunization (EPI) in 1978, and since then, both the variety and volume of vaccines in use have grown rapidly alongside broader promotion of immunization knowledge and heightened public awareness of proactively seeking vaccination information. Public demand has since expanded to encompass vaccine availability, rational immunization schedules, adverse event counseling, and personalized vaccination guidance — issues that have emerged as prominent focal points of public concern (*4*–*5*). In response, government consultation hotlines have evolved into vital, direct channels for public opinion monitoring and risk communication, enabling health authorities to promptly capture emerging needs and address public concerns as they arise.

As a rapidly urbanizing metropolis with a large and demographically diverse population, Suzhou faces unique complexities in immunization program management — most notably, coordinating cross-regional vaccination for migrant children and addressing varied demand for both EPI and non-EPI vaccines. This study analyzed immunization consultation hotline data from the Suzhou CDC spanning 2018 to 2024, with the goal of identifying key public concerns, persistent challenges, and emerging hot topics. The findings are intended to provide data-driven evidence for optimizing service allocation, refining targeted intervention strategies, and enhancing both the quality and responsiveness of EPI work in Suzhou.

METHODS

The Basic Information Hotline operates daily from 9:00 to 17:00, serving Suzhou City residents exclusively via telephone. All calls are handled by professionally trained staff who undergo regular training and are based at the Suzhou CDC. Hotline personnel collaborate closely with hospitals and vaccination clinics to address issues promptly — referring complex vaccination-related inquiries to specialists and managing complaint-related cases within designated feedback timeframes. Every call is answered on time by qualified professionals in a dedicated room, with all content recorded for subsequent reference and verification. The standardized workflow follows four sequential stages: call registration, data classification, results follow-up, and data archiving. Data were extracted from daily hotline records spanning a 7-year period (2018–2024). Only immunization-related valid calls (n=76,154) were included in the analysis; non-relevant inquiries — such as administrative, non-immunization issues — were excluded during preliminary screening. Two trained public health researchers independently reviewed the records to extract core topics, and any classification discrepancies were resolved through consultation with a third senior epidemiologist from Suzhou CDC.

Natural language processing (NLP) was applied to preprocess the text data, encompassing digitization, data cleaning, and removal of invalid information. This pipeline also defined categorical data features and computed term frequencies prior to systematic analysis. All structured outputs were organized in standard Microsoft Excel 2025 (Microsoft Corporation, headquartered in Redmond, USA). Descriptive statistical analyses — including frequency counts, constituent ratios, and temporal trends — were subsequently performed, and all figures were generated using Python (version 3.12.1, Python Software Foundation, based in Wilmington, USA).

RESULTS

Between 2018 and 2024, hotline call volume fluctuated and peaked at 15,365 in 2021 before declining sharply to 3,025 in 2024 — an 80% drop from the peak. The years 2019–2021 consistently sustained high volumes, each exceeding 13,937 calls per year (Figure 1A). Monthly call volumes exhibited clear seasonality, with peaks occurring from May through September and troughs in January and February (Figure 1B). Annual word clouds of consulted vaccines — in which font size reflects relative frequency — revealed distinct phase characteristics across the study period: during 2018–2019, high-interest vaccines centered on HPV, RV, DTaP-IPV-Hib, and pediatric/adult HepB; during 2020–2022, public inquiries shifted toward targeted pandemic-related concerns, while non-COVID-19 vaccine consultations declined significantly; and during 2023–2024, high-interest vaccines returned to pre-pandemic patterns (Figure 2). Figure 3 presents the year-by-year volume of vaccine-specific calls, organized into nine categories: Non-EPI vaccines (encompassing vaccination knowledge, vaccine safety, and protective efficacy); EPI vaccines; Supply and Price; Vaccination Services (including clinic locations, booking methods, and operating hours); adverse events following immunization (AEFI); Contraindications (contraindicated scenarios and vaccination for special populations); Vaccination Policy; Assessment Form-related; and COVID-19-related (Supplementary Tables S1–S2, available at https://weekly.chinacdc.cn/). Assessment form-related inquiries were the most frequent, accounting for 24,911 calls (32.71%), followed by vaccination services at 15,387 calls (20.21%) and vaccination policies at 15,026 calls (19.73%) (Figure 4).

DISCUSSION

This study represents the first long-term, continuous longitudinal analysis of government immunization consultation hotline calls in China, encompassing over 70,000 calls recorded in Suzhou between 2018 and 2024. The dataset serves as a measure of the overall effectiveness of immunization program hotlines, while also reflecting the concerns and advice-seeking behavior of self-initiated callers (*6*). Word cloud analysis and vaccine consultation frequency trend classification identified human papillomavirus vaccines (HPV), rabies vaccines (RV), and 13-valent pneumococcal conjugate vaccines (PCV13) as the hotspot vaccines. This pattern likely stems from early supply shortages and heightened public interest, both of which initially drove inquiry volumes upward, whereas subsequent supply stabilization and improved public health awareness contributed to a gradual decline in consultation volume (*7*).

In China, all childcare institutions, kindergartens, and primary schools are required to verify the vaccination certificates of newly enrolled children. Suzhou introduced digital support for this verification

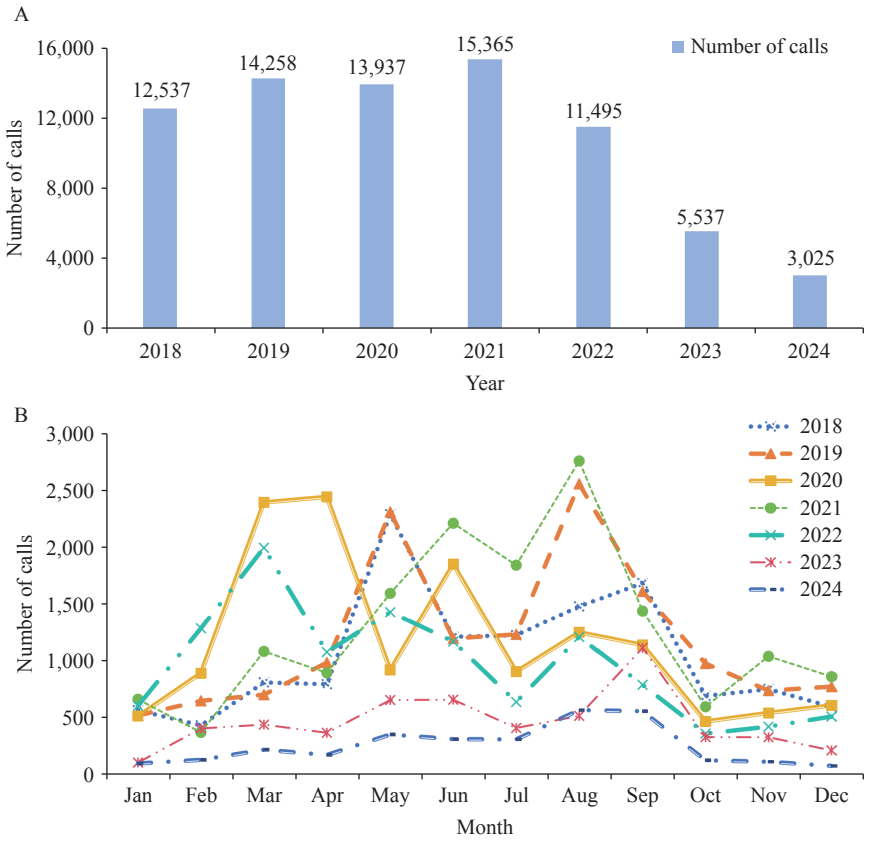

FIGURE 1. Hotline call volumes in Suzhou from 2018 to 2024. (A) Annual call counts; (B) Monthly call counts.

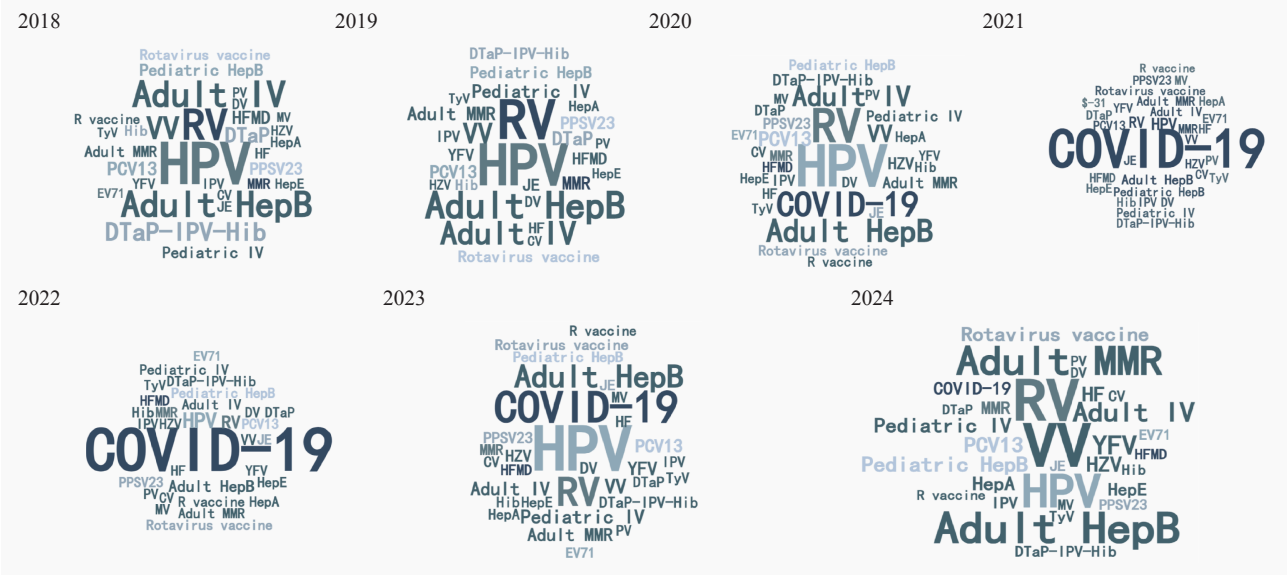

FIGURE 2. High-interest vaccines identified through annual word cloud analysis, Suzhou, 2018–2024.

process in 2016, whereby parents submitted printed vaccination assessment forms to schools for authentication during the designated enrollment period (May–September). Initially, both schools and parents were unfamiliar with the new system, which drove consultation volumes to a peak of 6,174 calls in 2019. However, city-wide awareness campaigns, professional training, and iterative system optimization gradually equipped parents and school staff with greater proficiency in the workflow, and related

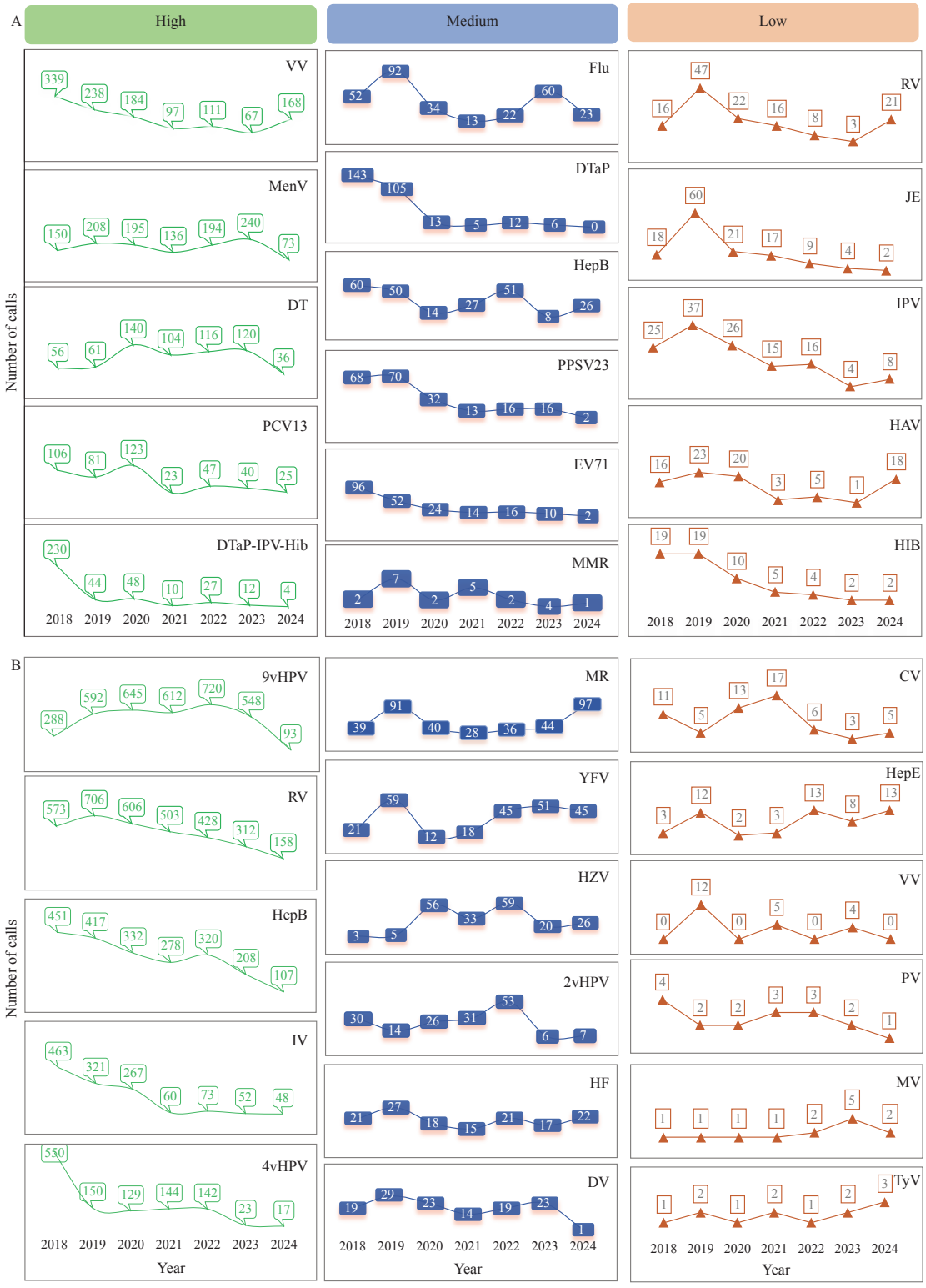

FIGURE 3. Frequency trend classification of consulted vaccines in Suzhou, 2018–2024. (A) Pediatric-related vaccines; (B) Adult-related vaccines.

Abbreviation: 2vHPV=2-valent Human Papillomavirus vaccine; 4vHPV=4-valent Human Papillomavirus vaccine; 9vHPV=9-valent Human Papillomavirus vaccine; CV=Cholera vaccine; DV=Dengue vaccine; HF=Hemorrhagic Fever vaccine; HepB=Hepatitis B vaccine; HEV=Hepatitis E vaccine; HZV=Herpes Zoster vaccine; IV=Influenza vaccine; MV=Malaria vaccine; MR=Measles and Rubella vaccine; MenV=Meningococcal vaccine; PV=Plague vaccine; RV=Rabies vaccine; TyV=Typhoid vaccine; VV=Varicella vaccine; YFV=Yellow Fever vaccine.

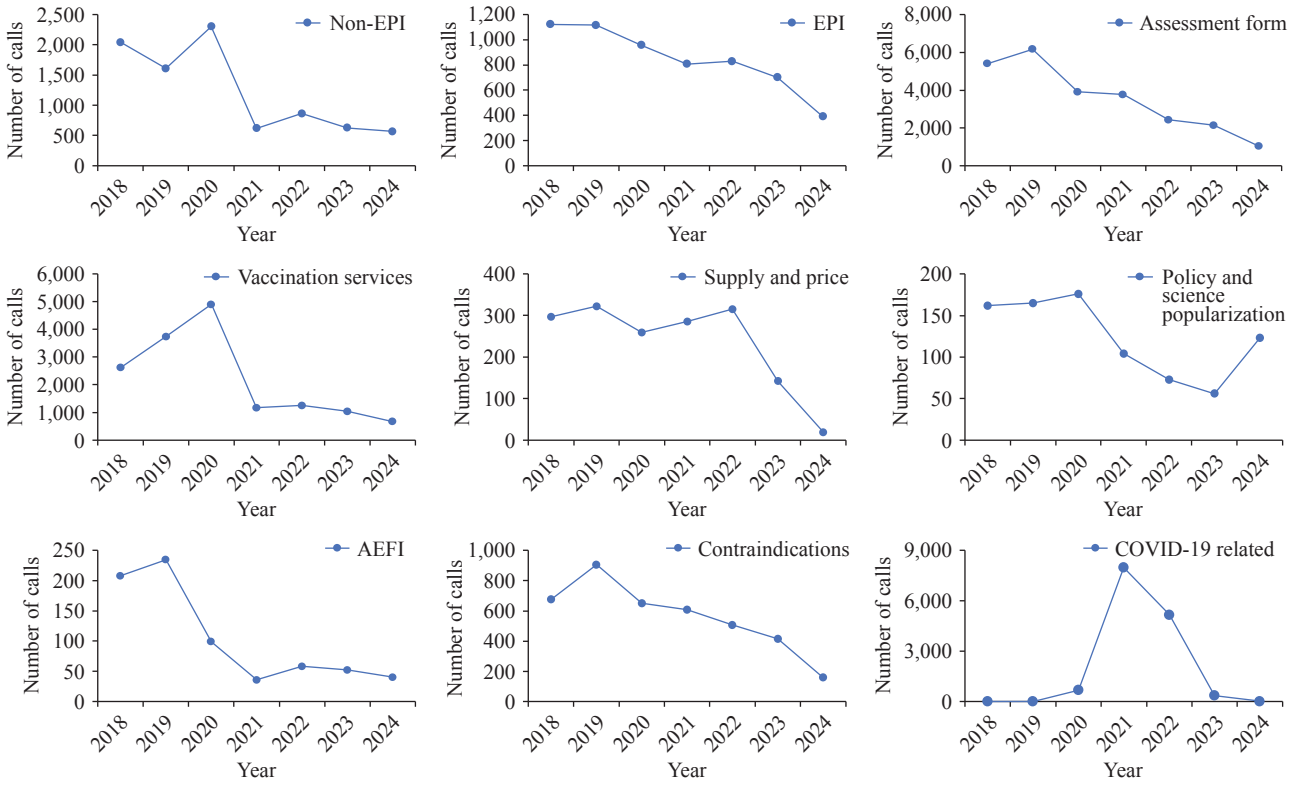

FIGURE 4. Annual trends in hotline call categories in Suzhou City, Jiangsu Province, China, 2018–2024.
Abbreviation: EPI=expanded program on immunization; AEFI=adverse events following immunization; COVID-19=coronavirus disease 2019.

consultation volumes began to decline steadily from 2020 onward. This downward trend indicates that the assessment form evaluation system has been progressively refined, thereby enhancing service accessibility (*8*–*10*). Nevertheless, vaccination certificate consultations remain a perennial focal point each year, owing to Suzhou's large floating population, whose newly arrived children require card registration and file establishment upon entry into the city's school system.

Vaccination services — encompassing the distribution of vaccination clinics, booking methods, and operating hours — along with non-EPI vaccines, including vaccination knowledge, vaccine safety, and protective efficacy, accounted for the most frequent consultation categories in 2020. This pattern is largely attributable to COVID-19-related disruptions, such as the suspension of clinic vaccination services and insufficient vaccine supplies during the pandemic. In Cambodia, the Hotline 115 system played a pivotal role in CCDC's response to and management of the COVID-19 pandemic (*11*). Consultations regarding vaccination policies emerged as the most frequent category in 2021, particularly those related to the implementation of relevant pandemic policies (*12*). Following 2020, the volume of immunization consultation hotline calls trended downward — a shift likely driven by the rapid advancement of the internet and digitalization, which has granted the public access to a diverse range of vaccination-related information channels (e.g., vaccination appointment mini-programs and WeChat Official Accounts), alongside optimized service delivery. The trends observed in vaccination services and vaccination policies reflect dynamic public demands, as well as the timeliness and effectiveness of local immunization service improvements, both of which may contribute to greater public willingness to vaccinate. Studies have demonstrated that enhanced vaccination knowledge among child guardians positively reduces vaccine hesitancy (*13*–*14*). The hotline therefore plays an indispensable role in immunization program communication, with staff professionalism and service quality serving as key factors in building public trust. Effective communication fosters a virtuous cycle of engagement — and over the years, our hotline service has earned widespread acclaim across all sectors of society.

This study has several limitations. The

immunization consultation hotline relies exclusively on verbal communication, which precludes the transmission of supplementary information such as text and images. Furthermore, consultations are constrained by call duration, and callers may face queuing delays during peak hours.

The hotline has supported immunization program across multiple dimensions. The declining call volume reflects positive feedback on improvements in work quality and efficiency, rather than a diminishment of service value. As social informatization continues to advance, public expectations for health service quality are rising, and vaccination concerns evolve alongside shifting public opinion trends (*13*). It is therefore essential to build professional, high-performing vaccination service teams and to deliver multi-channel, diversified consultation services capable of providing refined, personalized support. To this end, we propose the following practical recommendations: 1) strengthening the professional knowledge and competency of staff; 2) establishing a knowledge base for high-concern topics; 3) optimizing and expanding digital service platforms; and 4) intensifying public health education efforts. Together, these measures will enhance immunization service quality and advance public health outcomes in Suzhou.

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SUPPLEMENTARY MATERIAL

SUPPLEMENTARY TABLE S1. List of abbreviations.

Academic full name	Abbreviation
2-valent Human Papillomavirus vaccine	2vHPV
4-valent Human Papillomavirus vaccine	4vHPV
9-valent Human Papillomavirus vaccine	9vHPV
Cholera vaccine	CV
Dengue vaccine	DV
Hemorrhagic Fever vaccine	HF
Hepatitis B vaccine	HepB
Hepatitis E vaccine	HepE
Herpes Zoster vaccine	HZV
Influenza vaccine	IV
Meningococcal vaccine	MenV
Measles and Rubella vaccine	MR
Malaria vaccine	MV
Plague vaccine	PV
Rabies vaccine	RV
Typhoid vaccine	TyV
Varicella vaccine	VV
Yellow Fever vaccine	YFV

SUPPLEMENTARY TABLE S2. Frequently asked questions.

Category description	Example
Assessment form	How to update Assessment form information? How to download and print the assessment form?
Expanded program on immunization (EPI)	How to get vaccinated in Suzhou for children from other cities? I would like information on MMR. My child is due for it, but I am feeling unsure.
Non-expanded program on immunization (Non-EPI)	Is vaccination with non-EPI vaccines necessary?
Supply and Price	What is the cost of 9-valent HPV/DTaP-IPV-Hib vaccine?
Vaccination services	Opening hours of vaccination clinics
Adverse events following immunization (AEFI)	This child had DTaP-IPV-Hib at 3 months and had fever, how to manage? Should he have the next DTaP-IPV-Hib?
Contraindications	My child has Kawasaki, so does he get the Flu Vac?
Policy and Science Popularization	I was wanting to know who we can give HPV free to?
COVID-19 related	Where to get COVID-19 vaccine?

Methods and Applications

Development and Application of a Metabolic Health Index for the Chinese Population Aged 18 Years and Above

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ABSTRACT

Introduction: Metabolic health status plays a central role in the development of a broad spectrum of chronic diseases. Yet existing assessment approaches rely on comparatively complex measurement techniques, which constrain their widespread adoption and limits their utility in population-based metabolic health management.

Methods: The research employed a two-phase approach to construct a metabolic health index. We conducted a Delphi consultation to define and prioritize key metabolic health indicators, then drew on data from the China Chronic Disease and Risk Factor Surveillance, linked to the national mortality surveillance system, and built Cox proportional hazards models to estimate indicator-specific weights. Using these weights, we developed the Metabolic Health Index (MHI) and established a classification system to stratify metabolic health subtypes. We subsequently analyzed MHI score distributions and subtype prevalence across population subgroups.

Results: The Delphi process identified 11 indicators for inclusion in the model: age, smoking, alcohol consumption, body-mass index, waist-to-height ratio, fasting blood glucose, blood pressure, blood lipids, serum uric acid, metabolic-associated fatty liver disease, and family history of metabolic diseases. Applying the classification system, we identified 13 metabolic health subtypes across 7 categories. MHI scores declined with age, and females consistently outscored males across all age groups. Over half of the participants (54.5%) had relatively high MHI scores, and the proportion with higher scores decreased with age.

Conclusion: The MHI converts population health data into a quantitative metric for assessing metabolic health in adults and provides a practical approach for public health practice across diverse regions and settings.

The prevalence of metabolic diseases has risen steadily in recent years, driven by shifting lifestyle patterns and accelerating population aging (*1*). Projections indicate that by 2040, metabolic risk factors — including hypertension, elevated body mass index (BMI), and high fasting plasma glucose — will rank among the leading contributors to years of life lost worldwide (*2*). Currently, no consensus exists on a standardized definition of metabolic health (*3*). In clinical practice, metabolic health assessment largely follows the diagnostic criteria for metabolic syndrome, which rely on identifying specific abnormalities and satisfying a minimum threshold count (*4*). For the general population, however, systematic and quantifiable tools capable of comprehensive metabolic evaluation remain scarce, hampering early identification of at-risk individuals and timely intervention. To address this gap, the present study developed an evidence-based metabolic health assessment tool intended for public use — equipping individuals with the means to monitor their metabolic status, heighten health awareness, and take an active role in improving their own well-being through informed self-care.

METHODS

To select the 11 metabolic risk factors, we searched PubMed, the Cochrane Library, and the China National Knowledge Infrastructure (CNKI) for studies on metabolic risk factors associated with prominent health burden, covering the period from January 2015 to June 2024. We selected candidate factors according to three primary criteria: 1) relevance to metabolic diseases with substantial global health burden, 2) accessibility through standard health examinations or general public awareness, and 3) modifiability at the individual level. Applying these criteria, we identified nine directly modifiable risk indicators as core

candidates for the Delphi consultation: smoking, alcohol consumption, BMI, waist-to-height ratio (WHtR), fasting blood glucose (FBG), blood pressure, blood lipids, serum uric acid, and metabolic-associated fatty liver disease (MAFLD). To anchor the assessment within a personal risk context, we supplemented these nine indicators with two non-modifiable stratifiers: age and family history. Sex was excluded as a separate variable because the key metabolic differences attributable to sex — such as body fat distribution, lipid profiles, and hepatic steatosis—are more directly and actionably captured by specific indicators already included in our pool, namely WHtR, blood lipids, and MAFLD. In total, eleven indicators were carried forward into the Delphi consultation process.

We then invited nine experts with over 10 years of professional experience in medicine, nutrition, public health, and pharmacy to participate in a two-round Delphi survey to validate these indicators. The first round, conducted in June 2024, gathered data on expert demographics, self-rated authority, and opinions regarding the importance of each indicator. Experts rated the importance of each indicator on a 5-point Likert scale; any indicator that failed to reach sufficient consensus was re-evaluated in the second round to determine whether it should be retained. Enthusiasm was measured by the questionnaire response rate, while authority was quantified using the authority coefficient (Cr), calculated from the Coefficient of Familiarity (Cs) and the Coefficient of Judgment Basis (Ca). Agreement was evaluated using Kendall's W. All indices ranged from 0 to 1, with higher values indicating greater reliability. We further characterized the concentration of expert opinions through the mean, standard deviation, and coefficient of variation (CV) of the importance scores; indicators with a mean score below 3.5 or a CV above 0.25 were subject to re-evaluation in the second round. Complete consensus was defined as 100% agreement among all experts on the final indicator selection (*5*).

The study drew data from the China Chronic Disease and Risk Factor Surveillance (CCDRFS) (*6*). The CCDRFS employed multistage stratified cluster sampling across 31 provinces to ensure that the sample was representative of the general Chinese population. Mortality outcomes were ascertained from the National Mortality Surveillance System (NMSS), and the two datasets were linked using the resident ID number as the individual identifier. To protect participant confidentiality, resident IDs were subsequently removed from the linked dataset and replaced with anonymized serial numbers. We selected the 2018 wave of the CCDRFS for analysis because it represents the most recent available data and predates the COVID-19 pandemic, thereby avoiding the confounding influence of the pandemic on mortality outcomes. The final analytic sample comprised 184,509 adults drawn from 298 national Disease Surveillance Points (DSPs).

A mortality event was recorded if death occurred between the date of recruitment and the end of follow-up (censoring date: December 31, 2022). Data for the 11 candidate indicators were collected through a two-step process. First, trained staff obtained information on age, smoking status, alcohol consumption, and family history through structured face-to-face interviews. Second, a standardized physical examination was conducted to measure height, weight, waist circumference, FBG, blood pressure, blood lipids, and serum uric acid; BMI and WHtR were subsequently calculated from these anthropometric measurements. MAFLD status was determined in accordance with the international expert consensus statement (*7*).

To calculate indicator weights, we fitted a multivariable Cox proportional hazards model estimating associations between the 11 indicators and all-cause mortality. To facilitate practical public health application, we derived relative contribution weights directly from non-standardized regression coefficients (β) using the formula:

$$W_i = \left(\frac{\beta_i}{\sum_{j=1}^{11} \beta_j} \right) \times 100$$

After generating the weights, we applied the following formula to estimate the Metabolic Health Index score (MHI score):

$$MHI = \sum_{i=1}^{11} (W_i \times S_i).$$

W_i denotes the weight assigned to each indicator, whereas S_i represents its corresponding scoring function, which maps raw values to a normalized score between 0 and 1. We defined scoring rules a priori for each indicator type. For binary variables (e.g., family history), the score is either 0 (risk present) or 1 (risk absent). For ordinal or continuous variables, the scoring function distinguishes three risk states: optimal (score=1), suboptimal (score between 0 and 1, calculated via linear interpolation based on deviation from the optimal threshold), and salient risk (score=0).

We derived the specific thresholds defining each state from established clinical guidelines and consensus literature. The complete scoring algorithm is detailed in the Supplementary Table S1 (available at https://weekly.chinacdc.cn/).

To complement the single composite metric of the Metabolic Health Index (MHI) — which reflects overall metabolic status — we introduced the Metabolic Health Phenotype classification. We developed this framework on the basis of evidence that individuals with distinct metabolic profiles, such as metabolically healthy obesity or metabolically unhealthy normal weight, exhibit markedly different cardiometabolic risk levels (*8*). By capturing these phenotypic distinctions, the classification system provides actionable stratification for both public health practice and individual self-management.

The research applied this classification system, comprising 7 major categories and 13 specific subtypes, to all participants. We first dichotomized individuals as either "Metabolically Healthy" or "Metabolically At-Risk" based on core clinical indicators, then further subclassified those in the "At-Risk" group according to the specific patterns and severity of their risk factors (e.g., elevated fasting glucose and hypoglycemia) (Supplementary Table S2, available at https://weekly.chinacdc.cn/). Finally, we computed MHI scores for the entire sample and characterized the distributions of both the MHI and the metabolic health phenotypes — overall and stratified by sex and age group.

RESULTS

In the first round of the Delphi consultation, the questionnaire response rate reached 100%, with an authority coefficient of 0.96 and a Kendall's W of 0.906 (χ^2=224.646, P<0.001), reflecting high levels of expert enthusiasm, authority, and consensus. In this round, alcohol consumption (mean=3.375), total cholesterol (CV=0.327), and smoking (CV=0.359) failed to meet the inclusion criteria and were therefore re-evaluated in the second round. Following the second round, consensus was reached on all three indicators, and they were subsequently retained, resulting in the inclusion of all candidate indicators in the final MHI model.

The relative contribution weights of the indicators were distributed as follows: age (4.08%), smoking (12.37%), alcohol consumption (9.49%), BMI (1.27%), WHtR (4.91%), FBG (35.38%), blood pressure (9.96%), blood lipids (0.81%), serum uric acid (6.83%), MAFLD (7.74%), and family history (7.17%) (Figure 1).

The general population demonstrated moderate to high metabolic health levels, with MHI scores spanning an interquartile range of 66.59 to 86.26. Females consistently outscored males across all age groups, while scores generally declined with advancing age — though in certain strata, participants aged ≥70 years achieved higher scores than those in the 60–69 years group (Figure 2).

Further stratification by educational attainment and place of residence revealed a notable divergence by sex: among young women, higher educational attainment was associated with slightly elevated MHI scores, whereas among men, lower educational attainment corresponded to higher scores across most age groups (Supplementary Figure S1, available at https://weekly.chinacdc.cn/).

When scores were categorized into 10-point intervals, more than half of all study participants (54.5%) fell within the 71–90 range, and the proportion occupying higher score ranges declined progressively with age (Table 1).

Across all age groups, the "mixed risk" subtype accounted for the largest share of metabolic health subtypes, and its prevalence increased steadily with age. Marked sex differences were also evident: women displayed an overall healthier metabolic profile, with a substantially greater proportion classified as the "healthy" subtype (3.356% of women *vs.* 0.520% of men). In contrast, men exhibited a considerably higher prevalence of hyperuricemia (1.063% of men *vs.* 0.214% of women), while women were more prone to obesity-related conditions (1.213% of women *vs.* 0.396% of men) (Table 2).

DISCUSSION

In this study, we developed the MHI by integrating expert consensus with representative population data. Unlike conventional indicators that rely on a single biomarker or a binary diagnosis, this framework provides a comprehensive and continuous assessment of metabolic status. Specifically, the continuous MHI score overcomes the limitations of existing definitions by quantifying gradations of risk, thereby more faithfully reflecting the metabolic health landscape of the general Chinese population. Compared with existing metabolic assessment systems, the MHI offers a compelling combination of simplicity, practicality, and comprehensiveness. Its clearly defined and readily accessible indicators substantially lower application

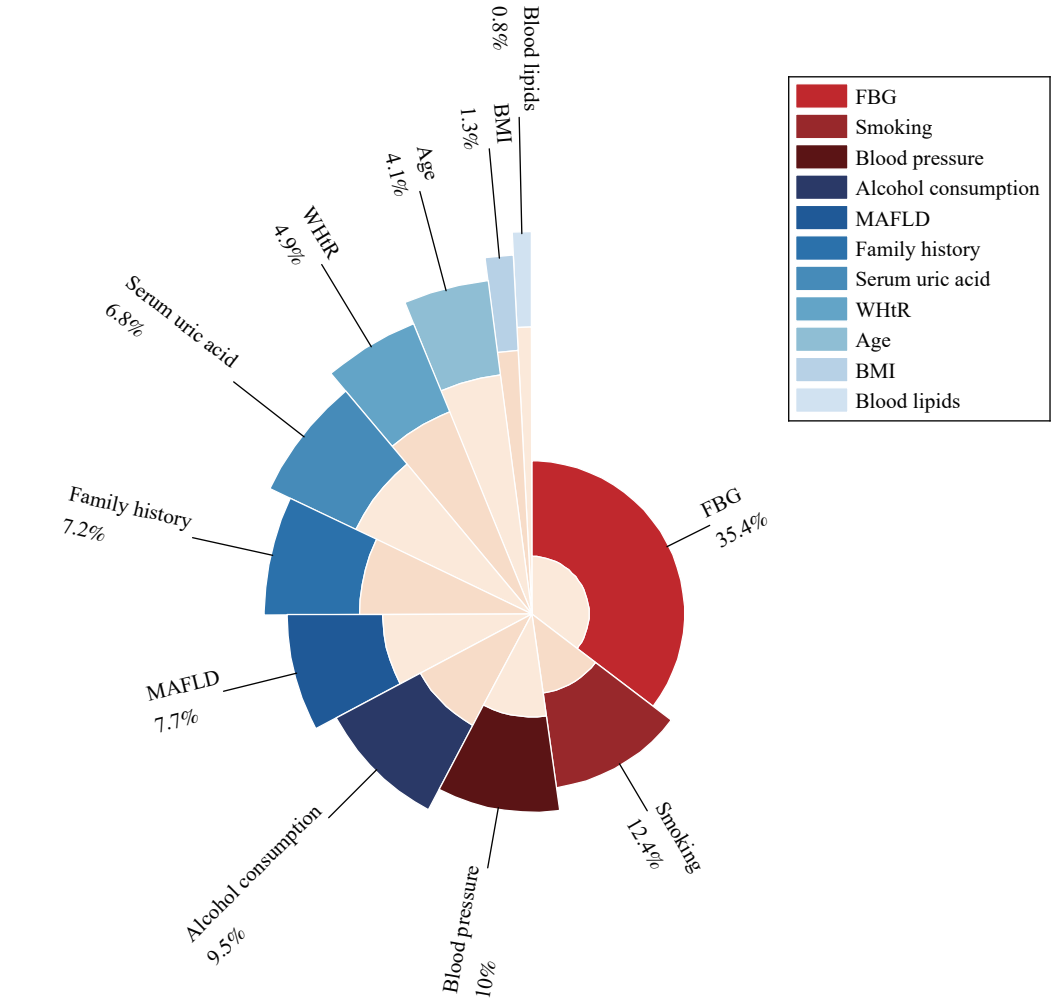

FIGURE 1. Distribution of weights assigned to the 11 MHI indicators.
Abbreviation: BMI=body mass index; WHtR=waist-to-height ratio; FBG=fasting blood glucose; MAFLD=metabolic dysfunction-associated fatty liver disease.

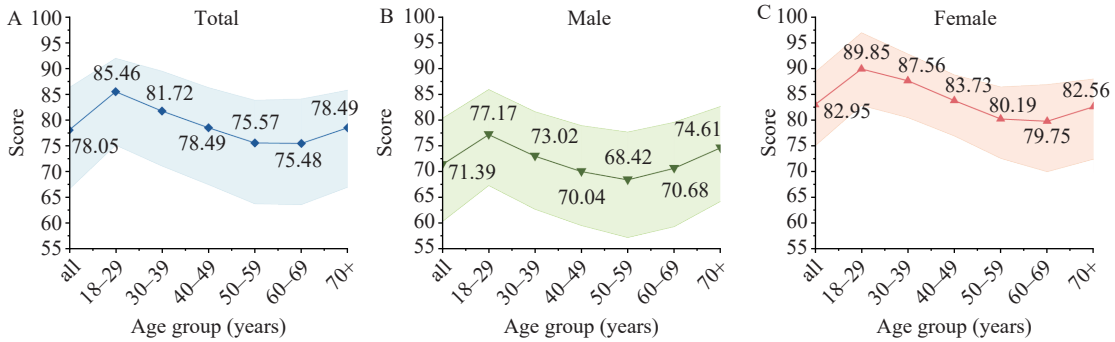

FIGURE 2. Age-related trends in MHI scores across different population groups. (A) Trends in MHI scores by age in the overall population; (B) Trends in MHI scores by age in males; (C) Trends in MHI scores by age in females.
Note: The shaded areas are the interquartile range.
Abbreviation: MHI=metabolic health index.

barriers and monitoring costs, providing an efficient solution for large-scale population screening. Moreover, the MHI more accurately captures the distributional characteristics of metabolic risk, enabling precise risk stratification and facilitating the early identification of sub-healthy individuals.

TABLE 1. MHI score distribution and population composition by age group (years).

Score	Age group (years), *n* (%)						
	18–29	30–39	40–49	50–59	60–69	70+	Total
≤10	1 (0.0)	3 (0.0)	17 (0.0)	23 (0.1)	28 (0.1)	8 (0.0)	80 (0.0)
11–20	12 (0.1)	54 (0.2)	177 (0.4)	271 (0.6)	232 (0.6)	45 (0.2)	791 (0.4)
21–30	67 (0.4)	145 (0.7)	465 (1.2)	796 (1.8)	742 (1.8)	244 (1.3)	2,459 (1.4)
31–40	159 (1.0)	326 (1.5)	952 (2.4)	1,639 (3.7)	1,853 (4.6)	722 (3.8)	5,651 (3.1)
41–50	321 (2.0)	660 (3.0)	1,732 (4.3)	2,541 (5.7)	2,465 (6.1)	1,236 (6.5)	8,955 (4.9)
51–60	746 (4.7)	1,424 (6.5)	2,935 (7.3)	3,716 (8.4)	3,094 (7.7)	1,268 (6.7)	13,183 (7.3)
61–70	1,553 (9.8)	2,458 (11.3)	5,412 (13.5)	6,851 (15.5)	6,122 (15.3)	2,143 (11.2)	24,539 (13.6)
71–80	2,750 (17.3)	4,586 (21.1)	10,296 (25.7)	12,238 (27.7)	10,757 (26.8)	4,656 (24.4)	45,283 (25.0)
81–89	4,907 (30.9)	7,153 (32.9)	12,620 (31.6)	11,795 (26.7)	10,382 (25.9)	6,510 (34.2)	53,367 (29.5)
≥90	5,356 (33.7)	4,951 (22.8)	5,389 (13.5)	4,348 (9.8)	4,445 (11.1)	2,219 (11.6)	26,708 (14.8)
Total	15,872 (100.0)	21,760 (100.0)	39,995 (100.0)	44,218 (100.0)	40,120 (100.0)	19,051 (100.0)	181,016 (100.0)

Abbreviation: MHI=Metabolic Health Index.

TABLE 2. Distribution of metabolic health subtypes in the population.

Subtype	Male, *n* (%)	Female, *n* (%)	Total, *n* (%)
High FBG A	92 (0.103)	96 (0.095)	188 (0.099)
High FBG B	55 (0.062)	44 (0.044)	99 (0.052)
Low FBG	128 (0.144)	230 (0.229)	358 (0.189)
Low UA	3 (0.003)	24 (0.024)	27 (0.014)
High UA	947 (1.063)	215 (0.214)	1,162 (0.613)
Dyslipidemia	1,301 (1.461)	1,889 (1.879)	3,190 (1.682)
Dyslipidemia–fatty liver risk	536 (0.602)	1,236 (1.229)	1,772 (0.935)
Low BP	352 (0.395)	1,168 (1.162)	1,520 (0.802)
High BP	7,463 (8.380)	7,004 (6.966)	14,467 (7.630)
Overweight/obese	353 (0.396)	1,220 (1.213)	1,573 (0.830)
Underweight	398 (0.447)	955 (0.950)	1,353 (0.714)
Healthy	463 (0.520)	3,374 (3.356)	3,837 (2.024)
Healthy–latent risk	2,343 (2.631)	3,164 (3.147)	5,507 (2.904)
Mixed metabolic risks	74,628 (83.793)	79,924 (79.492)	154,552 (81.513)

Abbreviation: FBG=fasting blood glucose; UA=uric acid; BP=blood pressure.

All-cause mortality serves as the endpoint for constructing the MHI, with data drawn from the NMSS. This approach yields reliable results that are less susceptible to information gaps and diagnostic variation. Given the absence of uniform standards for defining metabolic abnormalities, selecting specific metabolic outcomes risks confounding by missing data or interdependent indicators; using all-cause mortality therefore frees the MHI from dependence on any single metric or disease category. Further supporting this choice, the China National Mortality Surveillance Data Report (2021) shows that cardiovascular disease (CVD), cancer, and metabolic diseases collectively account for over 70% of all deaths (48.47%, 23.02%, and 3.12%, respectively). As the leading cause of death, CVD has a pathological basis largely rooted in metabolic dysfunction (*9*). With respect to cancer, recent evidence demonstrates that the global burden of metabolism-related tumors is rising, driven by elevated BMI and hyperglycemia (*10*). Together, these data indicate that all-cause mortality broadly captures the mortality risk attributable to metabolic abnormalities. Reinforcing this conclusion, a sensitivity analysis using metabolism-related mortality and metabolic health as alternative outcomes produced results highly consistent with those for all-cause mortality, further validating all-

cause mortality as a robust and representative surrogate indicator of metabolic health.

In the MHI model constructed using nationally representative data from the CCDRFS, FBG contributed the highest relative scores to the overall metabolic health assessment. This finding aligns with prior studies demonstrating that hyperglycemia is a key risk factor for disability and death, and that global fasting glucose levels and their associated disease burden continue to rise (*11*). Beyond glycemic status, the relative score distributions of the remaining indicators underscore the multidimensional nature of metabolic health (*12*), highlighting that effective population-level interventions must address multiple modifiable risk factors in concert rather than targeting any single variable in isolation.

To characterize population metabolic profiles comprehensively, we developed a dedicated classification system. By applying optimized threshold criteria, this system identifies individuals in a potential subclinical risk state, enabling targeted early intervention before metabolic dysfunction progresses to irreversible pathological changes.

MHI results revealed relatively high average scores across the study population. Paradoxically, however, subtype analysis identified mixed metabolic risk as the most prevalent metabolic phenotype, whereas the proportions of metabolically healthy individuals and other subtypes remained comparatively small. This discrepancy between elevated MHI scores and the high prevalence of mixed metabolic risk likely reflects the rigorous criteria applied to define optimal metabolic health. Accordingly, the MHI score and subtype classification capture complementary dimensions of metabolic status: the former quantifies the overall degree of health impairment, while the latter delineates specific patterns of risk. By doing so, this dual framework enhances the early detection of individuals with mild metabolic abnormalities, thereby supporting a strategic shift toward earlier and more targeted preventive interventions.

Notably, the age-related decline in MHI scores was evident across all sociodemographic strata, and males consistently exhibited lower MHI scores than females regardless of residential setting or educational attainment. This persistent sex difference likely reflects underlying biological predispositions (*13*) and a higher prevalence of adverse lifestyle behaviors among males (*14*). Educational attainment further revealed an inverse gradient in metabolic health among males, whereby lower educational levels corresponded to higher MHI scores. This seemingly paradoxical pattern may be partly explained by greater participation in high-intensity occupational physical activity among lower-educated manual workers, whereas more highly educated males tend to hold positions characterized by prolonged sedentary work (*15*).

Similarly, individuals aged ≥70 years exhibited higher mean MHI scores than those in the 60–69 age group. Although survivorship bias may partly account for this elevation in the oldest cohort, sensitivity analyses employing standardized coefficients further corroborated the primary findings. Together, these results indicate that the observed age-related trajectory is a robust phenomenon, independent of the specific scoring methodology applied.

Subtype distribution analysis further revealed clear age-dependent transitions: the prevalence of metabolically healthy individuals declined progressively with age, accompanied by a concomitant rise in mixed metabolic risk patterns. These shifts most likely stem from age-related physiological deterioration and the cumulative burden of metabolic risk factors over time (*16*).

Because it relies exclusively on routine, low-cost indicators, the index enables rapid risk stratification across diverse settings. Beyond its immediate utility in screening, the MHI serves as a robust instrument for evidence-based policy development and intervention planning. Its greatest potential for future implementation lies in integration within digital health infrastructures, where it can support dynamic surveillance and the long-term evaluation of chronic disease prevention programs.

Nevertheless, several limitations merit acknowledgment. The weights were derived to facilitate practical application, and their magnitudes are therefore influenced by measurement units; they should be interpreted primarily as contributions to the composite index rather than as absolute effect sizes. Although the data used in this study demonstrate reasonable representativeness, additional external validation is needed to confirm the model's generalizability across broader populations.

In summary, by integrating quantitative scoring with clinical characterization, the MHI provides a scalable, multidimensional framework for population-level health management. Future research should expand the model's applicability through continuous optimization across diverse regions, ultimately strengthening its utility for metabolic health assessment.

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SUPPLEMENTARY MATERIAL

SUPPLEMENTARY TABLE S1. Scoring methods for different types of metabolic-related indicators.

Indicator	Content/range	Scoring rule
Age	≥18 years	Scored dynamically within the age distribution according to deviation and weight
Smoking	Yes, daily	0 points
	Yes, not daily	1/3 weight
	Former smoker	2/3 weight
	Never smoked	Full score (weight)
Alcohol consumption	Yes, within past 30 days	0 points
	Yes, more than 30 days ago	1/2 weight
	Never	Full score (weight)
BMI	$18.5 \leq x < 24$	Full score (weight)
	$x \leq 15$ or $x \geq 28$	0 points
	$15 < x < 18.5$ or $24 \leq x < 28$	Scored dynamically by deviation and weight
WHtR	$0.4 \leq x < 0.5$	Full score (weight)
	$0.5 \leq x < 0.6$	Scored dynamically by deviation and weight
	$x \geq 0.6$ or $x < 0.4$	0 points
FBG	$3.9 \leq x < 6.1$	Full score (weight)
	$6.1 \leq x < 7.0$	Scored dynamically by deviation and weight
	$x < 3.9$ or $x \geq 7.0$	0 points
Serum uric acid	$120 \leq x < 360$	Full score (weight)
	$360 \leq x < 420$	Scored dynamically by deviation and weight
	$x < 120$ or $x \geq 420$	0 points
Blood pressure*		
SBP	$90 \leq x < 120$	Full score (weight)
	≥ 180	0 points
	< 90 or $120 \leq x < 180$	Scored dynamically by deviation and weight
DBP	$60 \leq x < 80$	Full score (weight)
	≥ 110	0 points
	< 60 or $80 \leq x < 110$	Scored dynamically by deviation and weight
Antihypertensive medication use	Yes	0 points
	No	Full score (weight)
Blood lipids†		
Total cholesterol	$x < 5.2$	Full score (weight)
	$5.2 \leq x < 6.2$	Scored dynamically by deviation and weight
	$x \geq 6.2$	0 points
Triglycerides	$x < 1.7$	Full score (weight)
	$1.7 \leq x < 2.3$	Scored dynamically by deviation and weight
	$x \geq 2.3$	0 points
LDL-C	$x < 3.4$	Full score (weight)
	$3.4 \leq x < 4.1$	Scored dynamically by deviation and weight
	$x \geq 4.1$	0 points

Continued

Indicator	Content/range	Scoring rule
HDL-C	x > 1	Full score (weight)
	0.5 < x ≤ 1	Scored dynamically by deviation and weight
	x ≤ 0.5	0 points
MAFLD[§]	Yes	0 points
	No	Full score (weight)
Family history[¶]	Yes	0 points
	No	Full score (weight)

Abbreviation: BMI=body mass index; WHtR=waist-to-height ratio; FBG=fasting blood glucose; SBP=systolic blood pressure; DBP=diastolic blood pressure; LDL-C=low-density lipoprotein cholesterol; HDL-C=high-density lipoprotein cholesterol; MAFLD=metabolic dysfunction–associated fatty liver disease.

* The lowest score among the three blood pressure indicators was taken.

† The lowest score among the four lipid indicators was taken.

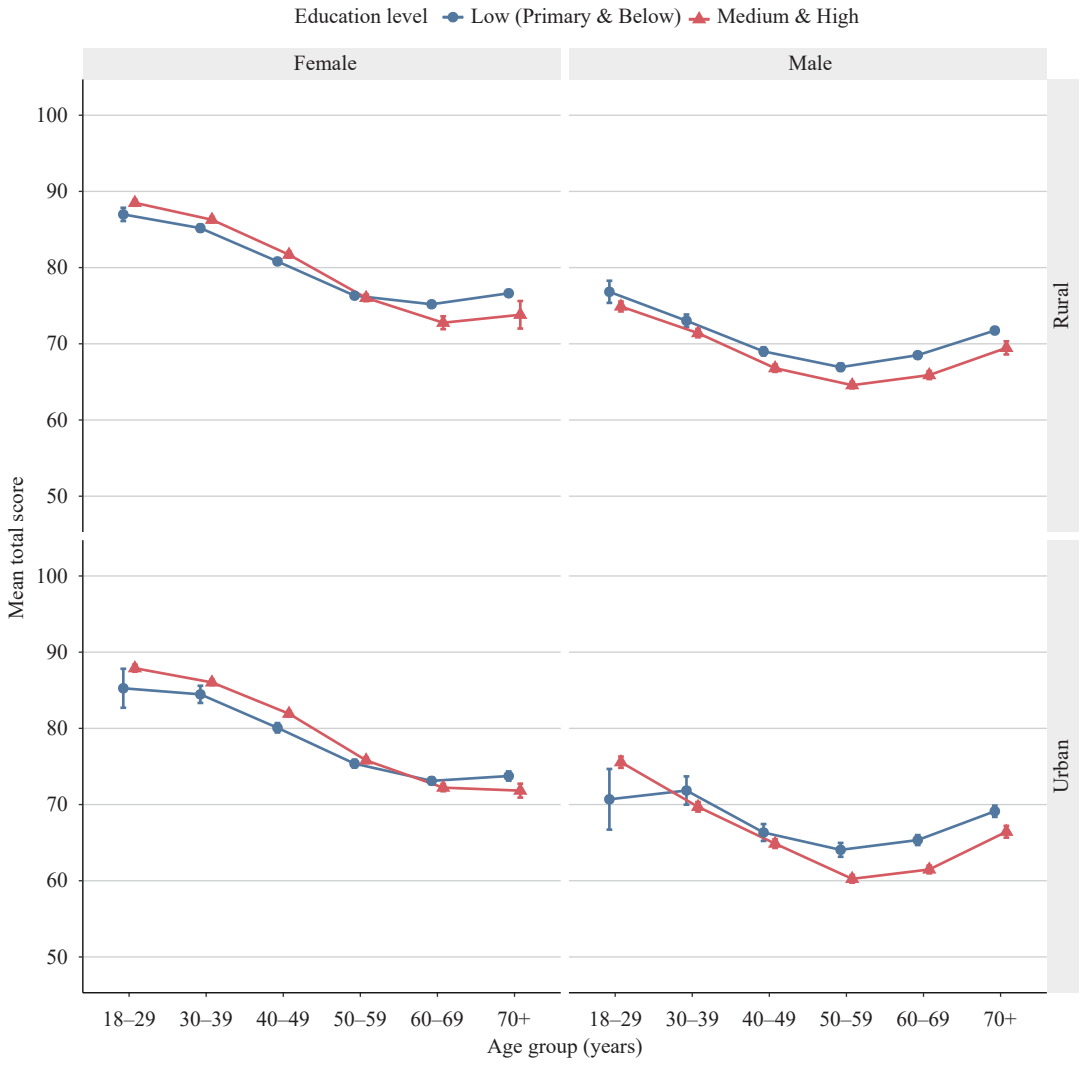
§ MAFLD was determined based on the MAFLD index. MAFLD definition: Diagnosis followed a two-step procedure. First, NAFLD was identified if the prediction score was ≥20. The score included a baseline of 6 points for Han ethnicity, plus: BMI (<23 kg/m^2=0, 23–<27.5=6, ≥27.5=9); Sex (Male=0, Female=1); Smoking (Current=0, Former=1, Never=2); Age (<65 y=8, 65–74=6, ≥75=0); and Diabetes (Yes=2, No=0). Second, MAFLD was diagnosed in NAFLD cases meeting at least one criterion: (1) Overweight/Obese (BMI≥23 kg/m^2); (2) Diabetes; or (3) Metabolic dysregulation in lean individuals (BMI<23 kg/m²). Metabolic dysregulation was defined as meeting≥2 of: Waist≥90/80 cm (M/F); BP≥130/85 mmHg or antihypertensive treatment; TG≥1.7 mmol/L or lipid-lowering treatment; HDL-C <1.0/1.3 mmol/L (M/F) or lipid-lowering treatment; Prediabetes (FBG 5.6–6.9 mmol/L or HbA1c 5.7%–6.4%); HOMA-IR≥2.5; or CRP>2 mg/L.

¶ Family history refers to diabetes or hypertension in first-degree relatives.

SUPPLEMENTARY TABLE S2. Classification system of metabolic health status.

Category	Subtype	Criteria
Glucose	High FBG A	FBG 6.1–6.9 mmol/L
	High FBG B	FBG ≥7.0 mmol/L
	Low FBG	FBG <3.9 mmol/L
Uric acid	Low UA	Uric acid <120 μmol/L
	High UA	Uric acid ≥360 μmol/L
Lipid	Dyslipidemia	Meeting any of the following four criteria: Total cholesterol ≥5.2 mmol/L Triglycerides ≥1.7 mmol/L LDL-C ≥3.4 mmol/L HDL-C ≤1.0 mmol/L
	Dyslipidemia-fatty liver risk	Confirmed fatty liver present
Blood pressure	Low BP	Without antihypertensive medication, and meeting at least one of the following: SBP <90 mmHg DBP <60 mmHg
	High BP	Meeting at least one of the following: SBP ≥120 mmHg DBP ≥80 mmHg Currently using antihypertensive medication
Weight	Overweight/obese	Meeting at least one of the following: BMI ≥24.0 kg/m² WHtR ≥0.5
	Underweight	Meeting at least one of the following: BMI <18.5 kg/m^2 WHtR <0.4
Healthy	Healthy	Smoking, alcohol consumption, and family history all “No”
	Healthy–latent risk	At least one of smoking, alcohol consumption, or family history is “Yes”
Mixed	Mixed metabolic risks	At least two risks among the following seven indicators: FBG, blood pressure, blood lipids, uric acid, fatty liver, BMI, WHtR

Abbreviation: BMI=body mass index; WHtR=waist-to-height ratio; FBG=fasting blood glucose; UA=uric acid; SBP=systolic blood pressure; DBP=diastolic blood pressure; LDL-C=low-density lipoprotein cholesterol; HDL-C=high-density lipoprotein cholesterol.



SUPPLEMENTARY FIGURE S1. Distribution of MHI score stratified by key demographics.
Abbreviations: MHI=metabolic health index.

Youth Editorial Board

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