

Assessing Physical Fitness and Health Efficiency in China: Temporal Dynamics, Spatial Spillovers, and Configurational Drivers

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1 **Assessing Physical Fitness and Health Efficiency in China: Temporal**
2 **Dynamics, Spatial Spillovers, and Configurational Drivers**

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Abstract

This study adopts an interdisciplinary framework to investigate the spatiotemporal evolution, spatial spillovers, and configurational pathways of physical fitness and health efficiency (PPEE) across 31 provincial-level regions in China from 2014 to 2023. PPEE was measured using a Super-SBM model incorporating undesirable outputs, with obesity prevalence included in the evaluation system. The Global Malmquist–Luenberger index was applied to decompose productivity changes, while the Spatial Durbin Model (SDM) and fuzzy-set QCA (fsQCA) were employed to identify spatial effects and configurational pathways, respectively. The results indicate that China’s PPEE remains relatively low, with a spatial pattern of higher levels in western regions, moderate levels in northeastern and central regions, and lower levels in eastern regions. PPEE improvement was primarily driven by technological progress, whereas efficiency catch-up remained limited. Spatial analysis revealed that healthcare expenditure share and the number of college students per 10,000 people negatively affected local PPEE; urbanization exhibited significant negative direct and spatial spillover effects, while per capita road area generated positive spatial spillovers. The fsQCA results demonstrated causal complexity and asymmetry, identifying resource adaptation and road infrastructure compensation pathways for PPEE improvement, while non-improvement was associated with insufficient resource transformation, structural constraints, and resource mismatches. These findings highlight that PPEE improvement depends on the synergistic

allocation and effective transformation of multiple resources, providing evidence for differentiated regional governance and cross-regional resource coordination.

Keywords: Physical fitness efficiency; place effects; regional health disparities; spatial spillovers; resource allocation; China

1 Introduction

With the continued implementation of the United Nations 2030 Agenda for Sustainable Development and its Sustainable Development Goals (SDGs), promoting health and improving population well-being has become a central objective of public policy and cross-sectoral collaborative governance worldwide [1-4]. Health is not only a fundamental prerequisite for individuals to achieve a high quality of life but also an important indicator of social development, economic sustainability, and national governance capacity [5, 6]. The World Health Organization (WHO) emphasizes that health should be understood as a positive and multidimensional state of well-being encompassing interrelated physical, psychological, spiritual, emotional, and social dimensions [7]. Against the backdrop of demographic shifts, lifestyle transitions, and the growing risk of chronic diseases, effectively improving population health has become a major challenge shared by countries worldwide.

Against this background, promoting population health is essential not only to address contemporary health risks but also to achieve long-term social sustainability. Physical fitness, as a key dimension of population health, provides a comprehensive measure of physiological functioning, physical performance, and the foundations for healthy development [8, 9]. However, socioeconomic development and lifestyle changes have contributed to insufficient physical activity, rising obesity prevalence, and an increasing risk of chronic diseases [10-13], posing growing challenges to population physical fitness. Accordingly, improving physical fitness through the efficient allocation of public resources has emerged as an important research priority in public health governance.

Physical activity is a key means of promoting population physical fitness,

improving health outcomes, reducing disease risk, and enhancing quality of life[14]. In recent years, countries worldwide have expanded the supply of sports resources by constructing sports facilities, strengthening public sports service systems, and promoting broad participation in physical activity [15]. However, increased investment in sports resources does not necessarily result in commensurate improvements in population physical fitness. Although sports infrastructure, public expenditure, and service provision create favorable conditions for physical activity and associated health outcomes [16, 17], regional disparities in economic development, demographic structure, resource allocation capacity, and governance models may lead to substantial differences in the efficiency with which sports resources translate into physical fitness outcomes [18, 19]. Therefore, evaluating public sports governance solely by resource inputs is no longer sufficient. A rigorous assessment of physical fitness and health efficiency is essential to optimize resource allocation and strengthen health governance.

As the world's largest developing country, China has experienced growing health demands amid rapid economic development and social transformation, bringing population physical fitness increasingly to the forefront of government and public concern. In recent years, China has advanced the Healthy China initiative and the national fitness strategy, with improving population health and ensuring equitable access to public sports services established as major development goals. Sustained investment in the sports sector has substantially expanded the supply of public sports resources, increased the availability of sports facilities, and strengthened the public sports service system [17]. Nevertheless, persistent regional inequalities, urban–rural disparities, and differences in resource-allocation efficiency have prevented sports-resource inputs and population physical fitness outcomes from being fully aligned across regions [20, 21].

More specifically, the development of population physical fitness in China exhibits pronounced regional heterogeneity. Although economically developed regions generally invest more heavily in sports resources, their efficiency in generating health outcomes is not necessarily higher because of population density,

lifestyle changes, and mounting pressure on resource utilization [18, 19, 22]. Conversely, some less-developed regions may achieve relatively high resource-conversion efficiency despite limited investment, owing to their lower initial resource endowments, reduced input redundancy, unmet health needs, and greater potential for marginal improvement [23]. PPEE is therefore determined not solely by the scale of resource inputs but also by economic development, population agglomeration, the alignment between infrastructure supply and demand, governmental capacity, and technological innovation. Identifying its spatiotemporal dynamics and underlying mechanisms is therefore essential to optimize the allocation of sports resources and promote coordinated regional health development in China.

In recent years, accelerating urbanization and continued lifestyle changes in China have made the determinants of PPEE increasingly complex. Economic and financial development can strengthen the resource base for sports facilities and public sports services, while advances in digital technology may improve the efficiency of public sports and health services by enhancing resource management and service delivery [24, 25]. Meanwhile, population agglomeration, industrial restructuring, and shifts in regional development patterns may reshape the effectiveness of sports-resource allocation [26, 27]. Moreover, because regions are interconnected through population mobility, resource sharing, and policy interactions, PPEE is not spatially isolated; changes in one region may generate spillover effects on neighboring regions [28, 29]. Nevertheless, several important limitations remain in the existing literature.

First, existing studies on population health and public sports services have mainly focused on health status, sports resource provision, and influencing factors, with limited attention to the efficiency of transforming sports-resource inputs into physical fitness outcomes [30]. Therefore, conventional input-based assessments cannot adequately capture regional differences in resource utilization efficiency [31]. Second, most studies adopt static evaluation approaches [32, 33], overlooking the dynamic evolution of PPEE and the respective roles of technological progress and efficiency improvement. As a result, the long-term development trajectory of PPEE in

China remains insufficiently understood. Third, previous research often treats regions as independent units and neglects spatial interactions arising from economic linkages, population mobility, and resource diffusion [34]. However, efficiency changes in one region may generate spillover effects on neighboring regions through spatial dependence [35, 36], highlighting the need to examine PPEE from a spatial network perspective. Finally, existing studies largely rely on single-factor or net-effect frameworks, which cannot fully capture the complex interactions among economic development, demographic structure, infrastructure, industrial environment, and technological innovation that jointly shape high PPEE outcomes [37, 38].

To address these research gaps, this study develops an integrated framework of “efficiency measurement–dynamic evolution–spatial spillovers–configurational identification” to systematically examine the spatiotemporal evolution and mechanisms of PPEE in China. Using panel data from 31 Chinese provinces during 2014–2023, this study constructs an input–output system with human resources, fiscal expenditure, and sports facilities as inputs; physical fitness achievement and regular exercise participation as desirable outputs; and obesity rate as an undesirable output. PPEE is measured using an undesirable-output Super-SBM model. The GML index is then applied to analyze dynamic changes in efficiency and identify their sources. Furthermore, the SDM is employed to examine direct and spatial spillover effects of key determinants, while fsQCA is used to identify configurational pathways leading to high PPEE through the interaction of multiple conditions.

This study contributes to the literature in four aspects. First, it develops an efficiency-based framework for evaluating PPEE, extending previous research beyond health-status assessment and revealing regional differences in the transformation efficiency of physical fitness and health resources. Second, it integrates the Super-SBM, GML, SDM, and fsQCA approaches to capture efficiency dynamics, spatial spillovers, and configurational mechanisms. Third, it advances understanding of PPEE formation by highlighting the roles of spatial interactions and multi-factor synergies. Finally, it identifies differentiated improvement pathways, providing empirical evidence for optimizing public sports resource allocation and promoting

coordinated regional health development.

2 Literature review

2.1 Measurement and evaluation of PPEE

Existing studies have investigated PPEE from the perspectives of indicator construction, evaluation methods, and influencing factors. However, differences in research objectives, spatial scales, and data availability have resulted in substantial heterogeneity in indicator selection and efficiency measurement approaches [39, 40]. Some studies focus on the allocation efficiency of fiscal investment, sports facilities, human resources, and public sports services [40], while others emphasize the inclusion of adverse health outcomes, such as obesity, as undesirable outputs in health efficiency evaluation [41]. Nevertheless, consensus has not yet been reached regarding the optimal evaluation framework. To address efficiency assessment involving multiple inputs, desirable outputs, and undesirable outputs, the undesirable-output Super-SBM model has been increasingly adopted. Based on the DEA framework, it integrates inputs, desirable outputs, and undesirable outputs into a unified system, enabling a more comprehensive evaluation of decision-making unit efficiency [42]. By incorporating negative health outcomes, it overcomes the limitations of conventional models that focus solely on desirable outputs and provides a more suitable approach for PPEE assessment [43-45]. Existing evidence further confirms its advantages in evaluating efficiency with multiple inputs, outputs, and undesirable outputs [46, 47]. Meanwhile, studies have revealed a coupling relationship between national fitness and population health, with considerable regional disparities shaped by fiscal investment, sports facilities, human resources, socioeconomic conditions, and other factors [48].

Compared with stochastic frontier analysis (SFA) and conventional CCR/BCC DEA models, the Super-SBM model has three key advantages. First, it accommodates both desirable and undesirable outputs, enabling adverse health outcomes to be incorporated into PPEE evaluation. Second, by incorporating slack variables, it provides a more accurate assessment of efficiency losses. Third, its super-efficiency

framework allows further discrimination among efficient decision-making units, making it suitable for provincial PPEE comparisons. Although SFA accounts for stochastic errors in efficiency estimation, it relies on predefined production functions and error distributions, limiting its flexibility in handling multiple inputs, outputs, and undesirable outputs. Given the multidimensional characteristics of physical fitness and health development, the Super-SBM model better aligns with the objectives and data structure of this study.

Building on the above, this study employs an undesirable-output Super-SBM model to estimate PPEE in China and constructs an evaluation indicator system consisting of inputs, desirable outputs, and an undesirable output (Table 1).

Table 1. Evaluation indicator system for PPEE.

Category	Dimension	Indicator	Definition	Reference
Input	Human Resource Input	Number of employees in urban units in the culture, sports, and entertainment sectors	Year-end number of persons employed in urban units in the culture, sports, and entertainment sectors in each province	[49, 50]
Input	Fiscal Resource Input	Expenditure on culture, sports, and media	Fiscal expenditure on public affairs related to culture, sports, and media in each province	[49, 50]
Input	Venue Resource Input	Sports venue area per capita	Ratio of the total area of sports venues to the permanent resident population in each province	[49, 51]
Input	Facility Resource Input	Number of sports venues	Total number of sports venues within the administrative	[49, 51]

Category	Dimension	Indicator	Definition	Reference
Desirable Output	Physical Fitness Level	Pass rate in physical fitness monitoring	area of each province Proportion of tested individuals whose comprehensive physical fitness assessment meets or exceeds the qualifying standard	[49]
	Participation in Physical Exercise	Proportion of the population regularly engaging in physical exercise	Proportion of the surveyed population meeting the national criteria for regular participation in physical exercise	
Undesirable Output	Health Risk	Obesity rate	Proportion of tested individuals classified as obese according to the applicable national physical fitness monitoring or health assessment standards	[52, 53]

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207 2.2 Spatial dependence and spillover effects of PPEE

208 The spatial effects of PPEE in China remain insufficiently explored, representing
209 an important gap in existing research. Previous studies have mainly focused on PPEE
210 measurement, regional disparities, and temporal dynamics, while paying limited
211 attention to interprovincial interactions and spillover mechanisms [54]. By treating
212 regions as independent units, these approaches cannot fully capture the cross-regional
213 transmission of PPEE. To address this issue, spatial econometric models have been

increasingly applied in studies of public sports services, population health, and health resource efficiency, providing useful tools for analyzing spatial effects of PPEE [22].

However, conventional spatial models have limitations. The spatial lag model mainly captures dependence in the dependent variable, whereas the spatial error model focuses on spatial correlation in the error term; neither can simultaneously identify how influencing factors affect local and neighboring regions [55, 56]. In contrast, the SDM incorporates spatial lags of both dependent and explanatory variables and decomposes effects into direct, indirect, and total effects [57, 58], enabling a more comprehensive analysis of PPEE spatial dependence and spillover mechanisms. Although SDM has been applied to eco-efficiency, public service efficiency, and health resource allocation efficiency [59-61], its application to PPEE in China remains limited, particularly regarding the systematic assessment of spatial spillovers from its determinants. Therefore, this study employs the SDM to examine the spatial effects of interprovincial PPEE in China and identify the differential impacts of healthcare investment, urbanization, education resources, green space, and infrastructure on local and neighboring regions. This approach extends previous studies beyond static measurement and regional comparison, providing deeper insights into the spatial interdependence and driving mechanisms of PPEE in China.

2.3 Configurational analysis of factors influencing PPEE

In recent years, qualitative comparative analysis (QCA) has emerged as an important approach for examining complex social, health, and environmental phenomena involving multiple interacting factors and causal relationships [62-64]. Among its variants, fsQCA has been widely applied in public health, resource allocation, and sustainability research because it identifies how combinations of conditions jointly produce specific outcomes [62, 65]. Unlike regression methods that focus on the marginal effects of individual factors, fsQCA adopts a set-theoretic approach to identify configurational pathways and equifinal solutions, making it suitable for analyzing causal complexity, asymmetry, and small- to medium-N samples. In PPEE research, conventional regression models generally estimate the net

effects of individual determinants while assuming linear relationships [51, 66], which may overlook interactions and nonlinear mechanisms among multiple factors. FsQCA overcomes this limitation by identifying necessary and sufficient conditions, as well as core and peripheral configurations, based on consistency and coverage measures [67, 68]. It further reveals how combinations of sports resources, public health services, population characteristics, technological progress, and policy factors jointly generate high or low PPEE outcomes [69, 70], providing insights for differentiated policy interventions. Therefore, this study applies fsQCA to identify configurational pathways underlying high and low PPEE under different combinations of conditions, offering evidence for improving PPEE, optimizing resource allocation, and promoting coordinated regional development.

3 Research methodology

3.1 Data sources

This study uses panel data from 31 provincial-level administrative regions in China during 2014–2023 to construct a PPEE evaluation system. The input indicators include human resources, fiscal expenditure, sports venue area, and sports facilities, while desirable outputs consist of physical fitness monitoring pass rates and regular exercise participation; obesity rate is included as the undesirable output. Data on physical fitness monitoring, exercise participation, and obesity rate were collected from official provincial government sources, statistical communiqués, and relevant annual reports, while other indicators were obtained mainly from the China Statistical Yearbook, China Health Statistics Yearbook, and provincial statistical yearbooks.

3.2 Research methods

3.2.1 Super-SBM model

This study employs an undesirable-output Super-SBM model to measure PPEE across Chinese provinces. The model incorporates input redundancies, desirable output deficiencies, and undesirable output excesses, while improving the discrimination of efficient decision-making units. Efficiency scores above 1 indicate leading provinces. Moreover, indicator weights are endogenously determined from

input–output data, minimizing subjective influence on the results.

The input and output indicators required for efficiency estimation are derived from the indicator system developed in this study (Table 1). This model enables the systematic measurement of PPEE across provinces and the identification of its stage-specific differences and evolutionary patterns. The model is specified as follows:

$$\begin{aligned}
\rho_G = \min & \frac{\frac{1}{k} \sum_{i=1}^k \frac{\bar{x}_i}{x_{i0}}}{\frac{1}{l_1+l_2} \left(\sum_{r=1}^{l_1} \frac{y_{r0}^g}{\bar{y}_r^g} + \sum_{t=1}^{l_2} \frac{\bar{y}_t^b}{y_{t0}^b} \right)} \\
s.t. & \quad \bar{x}_i \geq \sum_{j=1}^n x_{ij} \lambda_j, \quad i=1,2,\dots,k, \\
& \quad \bar{y}_r^g \leq \sum_{j=1}^n y_{rj}^g \lambda_j, \quad r=1,2,\dots,l_1, \\
& \quad \bar{y}_t^b \geq \sum_{j=1}^n y_{tj}^b \lambda_j, \quad t=1,2,\dots,l_2, \\
& \quad \lambda_j \geq 0, \quad \bar{x}_i \geq x_{i0}, \quad \bar{y}_r^g \leq y_{r0}^g, \\
& \quad \bar{y}_t^b \geq y_{t0}^b, \quad \bar{y}_r^g \geq 0, \quad \bar{y}_t^b \geq 0.
\end{aligned}$$

Where ρ_G denotes the super-efficiency score of PPEE; n is the number of decision-making units (DMUs). In the annual efficiency assessment, China's 31 provinces are treated as DMUs; thus, $n = 31$; k denotes the number of input indicators, with $k = 4$, including the number of employees in urban work units in the culture, sports, and entertainment sectors, expenditure on culture, sports, and media, per capita sports venue area, and the number of sports venues. l_1 denotes the number of desirable output indicators, with $l_1=2$, comprising the pass rate of physical fitness monitoring and the proportion of residents who regularly participate in physical exercise. l_2 denotes the number of undesirable output indicators, with $l_2 = 1$, namely the obesity rate. x_{i0} , y_{r0}^g , and y_{t0}^b represent the i th input, the r th desirable output, and the t th undesirable output of the province under evaluation, respectively. $\bar{x}_i$, $\bar{y}_r^g$, and $\bar{y}_t^b$ denote the corresponding super-efficiency projection values of the inputs, desirable outputs, and undesirable outputs, respectively. λ_j represents the intensity variable associated with the reference DMU. A higher ρ_G indicates a stronger capacity to

convert sports-related resource inputs into residents' physical fitness outcomes. When $\rho_G < 1$, the province has not reached the efficiency frontier and may exhibit input redundancy, insufficient desirable outputs, or an excessively high obesity rate. When $\rho_G = 1$, the province lies on the efficiency frontier. When $\rho_G > 1$, the province can moderately reduce its outputs while holding inputs constant, or moderately increase its inputs while holding outputs constant, while still maintaining an efficient status.

3.2.2 GML index

To evaluate the dynamic evolution of PPEE during 2014–2023, this study applies the GML index to measure total factor productivity changes. Based on the global production possibility set, the GML index incorporates desirable and undesirable outputs and is decomposed into Global Efficiency Change (GEC) and Global Technological Change (GTC) to identify productivity change sources. The formulas are as follows:

$$GML_t^{t+1} = \frac{1 + \vec{D}^G(x^t, y^t, b^t)}{1 + \vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1})} = GEC_t^{t+1} \times GTC_t^{t+1}$$

Where, x , y , and b denote the input, desirable output, and undesirable output vectors of a DMU, respectively; $\vec{D}^G$ denotes the directional distance function constructed from the global production possibility set; and GML_t^{t+1} measures the change in a province's total factor productivity in physical fitness from period t to period $t+1$. The GML index can be further decomposed into the GEC index and the GTC index. GEC captures the “catch-up effect” as a DMU moves closer to the production frontier, primarily reflecting changes in resource allocation and managerial efficiency. GTC captures shifts in the production frontier, indicating technological progress or regress. A value of $GML_t^{t+1} > 1$ indicates an improvement in total factor productivity in physical fitness, $GML_t^{t+1} = 1$ indicates no change, and $GML_t^{t+1} < 1$ indicates a decline. Similarly, $GEC_t^{t+1} > 1$ indicates efficiency improvement, whereas $GEC_t^{t+1} < 1$ indicates efficiency

deterioration. $GTC_t^{t+1} > 1$ signifies technological progress, whereas $GTC_t^{t+1} < 1$ signifies technological regress. Joint analysis of the *GML* index and its components therefore helps determine whether changes in PPEE in China are primarily driven by efficiency improvement or technological progress.

3.2.3 Construction of the spatial weight matrix

To capture transport-based interprovincial linkages and identify the spatial dependence of PPEE and the spillover effects of its determinants, this study constructs a road-distance-based spatial weight matrix for the SDM. Compared with contiguity or straight-line distance, road distance better reflects actual accessibility and spatial interaction costs. The matrix is specified as follows:

$$w_{ij}^{(1)} = \begin{cases} \frac{1}{d_{ij}}, & i \neq j, \\ 0, & i = j. \end{cases}$$

Where $w_{ij}^{(1)}$ denotes the spatial weight between provinces i and j ; d_{ij} denotes the road distance between the capital cities of provinces capitals. To minimize the influence of cross-provincial differences in aggregate spatial weights on model estimation, the road-distance-based spatial weight matrix was further row-standardized.

$$\tilde{w}_{ij}^{(1)} = \frac{w_{ij}^{(1)}}{\sum_{j=1}^N w_{ij}^{(1)}}$$

Where, $\tilde{w}_{ij}^{(1)}$ denotes the standardized spatial weight, and N denotes the number of provinces.

3.2.4 Spatial econometric model

To examine the spatial dependence of interprovincial PPEE in China and the spatial spillover effects of its determinants, this study specifies a SDM. The model incorporates spatial lags of both PPEE and its explanatory variables and employs a spatial weight matrix W_1 to capture interprovincial spatial linkages. This specification enables the identification of the direct effects of each determinant on

local PPEE and its spatial spillover effects on other regions. The model is specified as follows:

$$PPEE_{it} = \rho W_1 PPEE_{it} + \beta X_{it} + \theta W_1 X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where $PPEE_{it}$ denotes $PPEE$ in province i in year t ; X_{it} is a vector of explanatory variables, including the share of healthcare expenditure, the urbanization rate, the number of college students per 10,000 people, the green coverage rate of built-up areas, and per capita road area; and W_1 denotes the spatial weight matrix. $W_1 PPEE_{it}$ and $W_1 X_{it}$ represent the spatial lags of $PPEE$ and the explanatory variables, respectively. ρ is the spatial autoregressive coefficient; β and θ are the coefficients of the explanatory variables and their spatial lags, respectively; μ_i and λ_t denote province and time fixed effects, respectively; and ε_{it} is the idiosyncratic error term.

3.2.5 Fuzzy-Set Qualitative Comparative Analysis

This study employs fsQCA to examine how configurations of multiple conditions lead to the improvement or non-improvement of PPEE. First, the outcome and antecedent conditions are calibrated into fuzzy sets, followed by a necessary-condition analysis and truth-table construction to identify configurations with high consistency. On this basis, multiple configurational pathways associated with PPEE improvement and non-improvement are identified, revealing the complex causal mechanisms arising from different combinations of conditions.

3.3 Selection of influencing factors

To identify the mechanisms shaping PPEE across provinces, this study draws on the variable-selection approaches adopted in previous research on physical fitness and health, public health, and regional efficiency. Considering the practical mechanisms underlying PPEE and data availability, five influencing factors are selected: healthcare expenditure share, urbanization rate, the number of college students per 10,000 people, green coverage rate of built-up areas, and per capita road area (Table 2).

Table 2. Determinants of PPEE.

Dimension	Indicator	Definition	Reference
Healthcare investment	Healthcare expenditure share	The proportion of healthcare expenditure in the general public budget expenditure, reflecting the priority assigned to healthcare investment.	[71]
Urbanization	Urbanization rate	The proportion of the urban permanent population in the total permanent population, reflecting the level of regional urbanization.	[72]
Higher education resources	College students per 10,000 people	The number of students enrolled in higher education institutions per 10,000 permanent residents, reflecting regional higher education resources and human capital.	[71, 73]
Urban green environment	Green coverage rate of built-up areas	The proportion of green-covered land in the total built-up area, reflecting urban green-space provision and ecological conditions.	[74, 75]
Road infrastructure	Per capita road area	Urban road area per permanent resident, reflecting road infrastructure provision and transportation accessibility.	[74, 76]

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377 **4 Results**

378 **4.1 PPEE measurement results**

379 Based on panel data for 31 provincial-level administrative regions in China from
380 2014 to 2023, the Super-SBM model incorporating undesirable outputs was employed
381 to estimate provincial PPEE, as presented in Figure 1. Overall, PPEE exhibited
382 pronounced stage-specific fluctuations, accompanied by substantial interprovincial
383 and regional disparities. The national average declined from 0.5880 in 2014 to 0.5347
384 in 2023, representing a cumulative decrease of 9.06%, while the overall mean during
385 the study period was 0.5074. These findings indicate considerable scope for
386 improving resource allocation and input–output conversion efficiency in promoting
387 physical fitness.

From a temporal perspective, national PPEE generally improved between 2014 and 2015, with most provinces recording efficiency scores between 0.3 and 0.7, while only a few—such as Hainan, Guizhou, Yunnan, and Tibet—exceeded 1. From 2016 to 2018, national PPEE declined continuously, with most provincial scores falling below 0.5 and the number of super-efficient provinces decreasing from two to zero. Between 2019 and 2023, PPEE exhibited a fluctuating recovery: the number of super-efficient provinces increased from three in 2019 to nine in 2022 before declining to five in 2023. During the latter period, high-efficiency provinces were predominantly concentrated in western China. Overall, PPEE displayed pronounced stage-specific fluctuations throughout the study period, accompanied by persistent interprovincial disparities.

Substantial interprovincial disparities in PPEE were observed. Over the study period, Tibet, Ningxia, Hainan, and Qinghai recorded relatively high mean efficiency scores of 0.9857, 0.9120, 0.7855, and 0.7844, respectively. Notably, PPEE exceeded 1 in Tibet for seven years and in Ningxia for five years, indicating strong resource allocation and output conversion capabilities. By contrast, Jiangsu, Beijing, Zhejiang, and Shandong exhibited relatively low mean scores of 0.2479, 0.2888, 0.2925, and 0.3100, respectively, and none achieved super-efficiency during the study period. Moreover, several provinces experienced substantial fluctuations. For example, Hainan's PPEE declined from 1.7247 in 2015 to 0.4608 in 2023, whereas Guizhou's increased from 0.0887 in 2017 to 1.2288 in 2022. These variations reveal pronounced stage-specific differences across provinces in the allocation of physical fitness resources and improvements in PPEE.

From a regional perspective, western China maintained a relatively high level of PPEE, while the northeastern and central regions exhibited moderate levels, and the eastern region lagged behind. Specifically, western China recorded a mean PPEE of 0.6592 over the study period, with Tibet, Ningxia, Qinghai, Yunnan, and Guizhou performing particularly well, despite persistent intraregional disparities. The northeastern and central regions reported mean PPEE scores of 0.4516 and 0.4218, respectively, indicating moderate but fluctuating performance. By contrast, eastern

China had the lowest mean PPEE, at 0.3934. Within this region, Hainan and Tianjin performed relatively well, whereas Beijing, Jiangsu, Zhejiang, and Shandong recorded comparatively low efficiency scores, indicating substantial intraregional heterogeneity. Overall, the spatial pattern was characterized by higher PPEE in western China, moderate levels in the northeastern and central regions, and lower levels in eastern China, highlighting pronounced regional disparities and uneven development in China's PPEE.

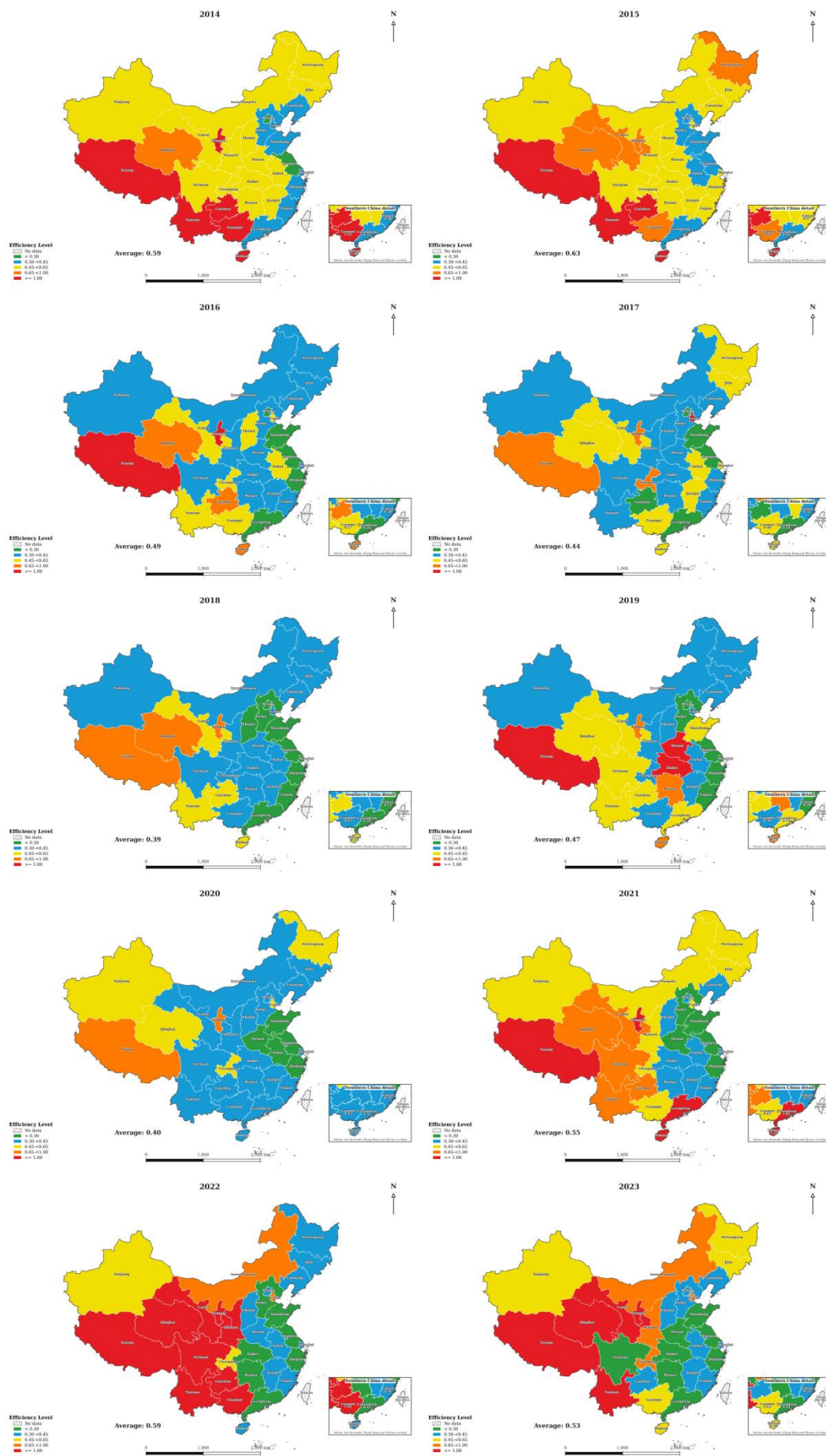


Figure 1. Spatial distribution of PPEE across 31 provincial-level regions in China, 2014–2023.

4.2 GML index for PPEE

To dynamically assess the intertemporal evolution of provincial PPEE, this study calculates the GML index under the global frontier framework and decomposes it into the efficiency change index (EG) and technological change index (TG), as illustrated in Figure 2. A GML value greater than, equal to, or less than 1 indicates an improvement, no change, or a decline in PPEE over time, respectively. An EG value greater than 1 signifies efficiency improvement and a positive catch-up effect, whereas a TG value greater than 1 indicates technological progress, reflected by an outward shift of the production frontier.

From a temporal perspective, provincial GML indices exhibited pronounced fluctuations and stage-specific divergence between 2015 and 2023, characterized by alternating periods of improvement and decline in PPEE. In 2015, most provinces recorded GML values above 1, although the magnitude of improvement varied considerably. During 2016–2017, GML values declined in most provinces, while a small number maintained growth. The 2018–2019 period featured mixed patterns of improvement and deterioration, with several provinces recording relatively high GML values in 2019. Interprovincial disparities widened further in 2020, as substantial increases in some provinces coincided with marked declines in others. In 2021, most provinces reported GML values above 1, albeit with considerable variation in the magnitude of improvement. The overall improvement continued in 2022, whereas provincial divergence re-emerged in 2023, with some provinces recording GML values above 1 and others falling below 1.

The decomposition results reveal that EG and TG contributed differently across years and provinces. In 2015, GML growth in some provinces was primarily driven by improvements in EG, whereas in others it was mainly attributable to increases in TG. In 2016, the national average GML index declined to 0.7858, accompanied by a TG value of 0.6670, indicating that the deterioration in PPEE was largely associated with technological regress. By contrast, the national average GML index reached

1.3853 in 2021, with TG rising to 1.4443, suggesting that the improvement was predominantly driven by an outward shift of the technological frontier. In 2023, TG increased to 1.2880, while EG declined to 0.9354, resulting in a decrease in the GML index to 0.9891. This finding indicates that the positive effect of technological progress was constrained by insufficient efficiency catch-up. Overall, improvements in PPEE during the study period were driven by either EG or TG, with substantial heterogeneity across years and provinces.

From a regional perspective, the eastern coastal provinces and several western provinces recorded GML values above 1 in multiple years, indicating relatively pronounced improvements in PPEE. The central provinces generally experienced alternating periods of improvement and decline, while Northeast China remained broadly stable despite some interannual fluctuations. The western and border provinces exhibited comparatively greater volatility, with substantial improvements or marked declines in certain years. These findings demonstrate that the intertemporal evolution of provincial PPEE in China is characterized by pronounced asynchrony, stage-specific variation, and regional differentiation.

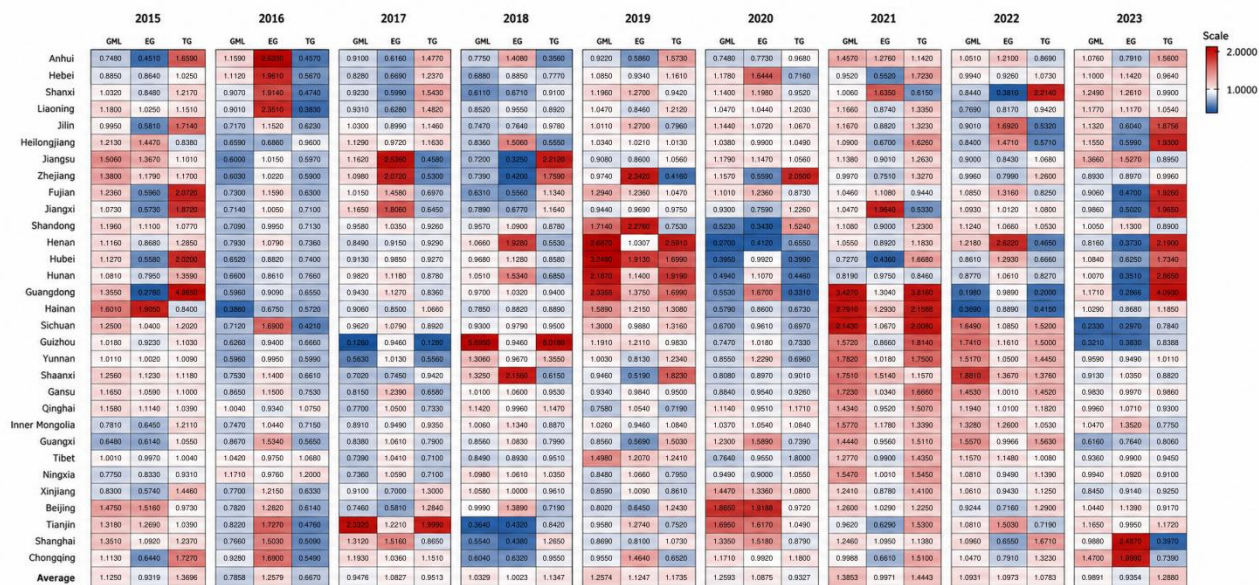


Figure 2. Temporal dynamics and drivers of PPEE in China, 2014 – 2023: Decomposition of the GML Index.

4.3 Construction and analysis of the SDM

4.3.1 Specification and testing of the spatial panel model

To address potential estimation bias caused by multicollinearity, a VIF test was conducted for all explanatory variables. As shown in Table 3, all VIF values are below 3, with the highest value observed for the urbanization rate (2.02). Given the commonly accepted threshold of $VIF < 10$, no serious multicollinearity exists among the explanatory variables, supporting their suitability for subsequent econometric analyses.

Second, the spatial dependence of PPEE was examined before estimating the spatial panel model. Global Moran's I was used to assess the spatial autocorrelation of provincial PPEE in China from 2014 to 2023 (Table 4). The results show that Moran's I is significant at the 5% level in all years, indicating a non-random spatial distribution of PPEE and supporting the application of spatial panel models to further analyze spatial spillover effects.

Given the significant spatial dependence of PPEE, a spatial panel econometric model was constructed. A series of specification tests was conducted to determine the appropriate model form (Table 5). An OLS model without spatial effects was first estimated, followed by LM and robust LM tests for spatial lag and error dependence. Wald and LR tests were then applied to assess whether the SDM could be simplified to SAR or SEM, while the Hausman and LR tests were used to determine the appropriate effects specification. The results show that the LM-error, Robust LM-error, LM-lag, and Robust LM-lag statistics are all significant at the 5% level, confirming the coexistence of spatial lag and spatial error dependence. Wald and LR tests reject the hypotheses that the SDM can be reduced to SAR or SEM at the 1% level. The Hausman test also rejects the random-effects specification, supporting the fixed-effects SDM. Based on the LR tests for individual and time effects, a two-way fixed-effects SDM was ultimately selected for subsequent regression analysis and spatial effect decomposition.

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Table 3. Results of the multicollinearity test.

Variable	VIF	1/VIF
Healthcare expenditure share	1.25	0.8016
Urbanization rate	2.02	0.4962
College students per 10,000 people	1.58	0.6341
Green coverage rate of built-up areas	1.47	0.6818
Per capita road area	1.25	0.7987
Mean VIF	1.51	

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Table 4. Global spatial autocorrelation.

year	I	E(I)	Sd(I)	Z	P-value
2014	0.3390	-0.0333	0.0634	5.8780	0.0000***
2015	0.2170	-0.0333	0.0572	4.3733	0.0000***
2016	0.3154	-0.0333	0.0611	5.7111	0.0000***
2017	0.0971	-0.0333	0.0611	2.1343	0.0328**
2018	0.3421	-0.0333	0.0615	6.1079	0.0000***
2019	0.1823	-0.0333	0.0625	3.4522	0.0006***
2020	0.2704	-0.0333	0.0617	4.9257	0.0000**
2021	0.4138	-0.0333	0.0630	7.0928	0.0000***
2022	0.3984	-0.0333	0.0642	6.7211	0.0000***
2023	0.3308	-0.0333	0.0637	5.7149	0.0000***

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Note: ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

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Table 5. Diagnostic tests for the spatial panel econometric model.

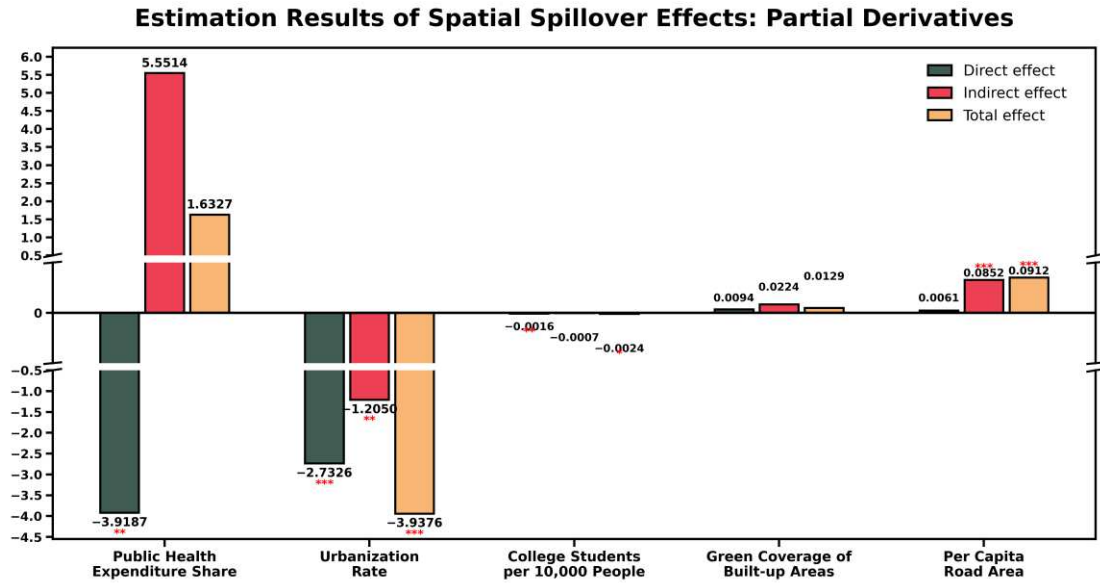
Test	Test Item	Statistic	p-value
LM Test for Spatial error	Lagrange multiplier	125.852	0.000***

	Robust Lagrange multiplier	101.440	0.000***
LM Test for Spatial lag	Lagrange multiplier	28.721	0.000*
	Robust Lagrange multiplier	4.310	0.038**
LR-Test	Both-Ind	20.92	0.0019***
	Both-Time	154.43	0.0000***
Wald-Test	Wald Test for SAR	23.17	0.0003***
	Wald Test for SEM	21.30	0.0007***
LR-Test	SAR–SDM	23.42	0.0003***
	SDM–SEM	23.40	0.0003***
Hausman test		19.51	0.0003***

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3.2 Direct effect analysis

As shown in Figure 3, the direct effects of the share of healthcare expenditure, urbanization rate, and number of college students per 10,000 people are all significantly negative, with coefficients of -3.9187 , -2.7326 , and -0.0016 , respectively. The urbanization rate is significant at the 1% level, while the other two variables are significant at the 5% level. These findings suggest that increased healthcare expenditure has not yet been effectively translated into improvements in physical fitness and health efficiency; rapid urbanization may place additional pressure on the allocation of health resources through population concentration and rising demand for public services; and the concentration of higher education resources has not been fully converted into broader physical fitness and health outcomes.



Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The broken y-axis magnifies effects close to zero.

Figure 3. Direct and spatial spillover effects of factors influencing PPEE in China: evidence from the SDM.

4.3.3 Spillover effect analysis

As shown in Figure 3, the urbanization rate exhibits a significant negative spatial spillover effect on PPEE in neighboring regions. Its indirect effect is -0.8368 and is statistically significant at the 1% level, indicating that increases in urbanization may negatively affect PPEE in adjacent regions.

Per capita road area demonstrates a significant positive spatial spillover effect on PPEE in neighboring regions. Its indirect effect is 0.0895 and is statistically significant at the 1% level, indicating that increases in per capita road area contribute to improvements in PPEE in adjacent regions.

4.3.4 Robustness checks

To further assess the robustness of the estimation results, a robustness test was conducted by replacing the spatial weight matrix. While keeping the model specification and estimation approach unchanged, the highway-distance-based spatial weight matrix used in the baseline regression was replaced with an economic-distance-based spatial weight matrix. The SDM was then re-estimated using the spatial fixed-effects transformation approach proposed by Lee and Yu (2010)

[77]. The corresponding results are presented in Table 6.

The results show that, after replacing the spatial weight matrix, the directions of the estimated effects remain largely consistent across variables. The local effects of the share of healthcare expenditure and the urbanization rate remain significantly negative, while the spatial lag effect of per capita road area remains significantly positive, confirming its stable positive spatial spillover effect. Meanwhile, the spatial autoregressive coefficient (ρ) remains significantly positive under different model specifications, further supporting the existence of spatial dependence in PPEE.

Table 6. Robustness test results

Variable	Geographic Distance				Economic–Geographic			
	Main	P-value	Wx	P-value	Main	P-value	Wx	P-value
Healthcare expenditure share	-4.8153	0.005***	5.6746	0.078*	-3.2517	0.038**	0.4146	0.89
Urbanization rate	-2.5309	0.000***	—		-2.7931	0.000***	—	
College students per 10,000 people	-0.0016	0.039**	—		-0.0011	0.173	—	
Green coverage rate of built-up areas	-0.0125	0.219	0.02	0.442	-0.005	0.571	0.0212	0.695
Per capita road area	-0.0071	0.3	0.0678	0.000***	0.0072	0.251	0.0732	0.035**
Spatial ρ	0.3418	0.000***			0.6162	0.000***		
σ^2_e	0.0237	0.000***			0.0269	0.000***		

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.4 fsQCA-Based Configurational Analysis

4.4.1 Data calibration

The fsQCA method is grounded in set theory and Boolean algebra and requires all data to be calibrated to values within the interval [0,1]. Because the raw data collected in this study do not satisfy this requirement, calibration is performed before the formal analysis. Following Fiss (2011) [78], the thresholds for full membership,

the crossover point, and full non-membership are set at the 75th, 50th, and 25th percentiles, respectively. Moreover, to avoid logical ambiguity and uncertainty in binary classification, calibrated values of 0.500 are adjusted to 0.501 following Fiss (2011) [78] and Cangialosi (2023) [79]. The calibration results for the variables associated with PPEE are presented in Table 7.

Table 7. Variable calibration points

Variable	Fact calibration anchor points		
	75 % full in	50 % crossover point	25 % full out
Healthcare expenditure share	0.0946	0.0856	0.0726
Urbanization rate	0.6767	0.6091	0.5432
College students per 10,000 people	255.1003	216.5655	182.3988
Green coverage rate of built-up areas	42.6750	40.9000	38.4000
Per capita road area	21.3350	17.4100	14.5400

4.4.2 Necessary condition analysis

Following Schneider and Wagemann (2010) [80], an antecedent condition is considered necessary when its consistency exceeds 0.90. Although no minimum threshold has been established for coverage, conditions or configurations with coverage values close to zero are generally regarded as having negligible relevance to the outcome. This study calculates the consistency and coverage of the necessary conditions for high and non-high PPEE (Table 8). The results show that the consistency values of all five conditions and their negations are below 0.90 for both outcomes. Thus, none of these conditions or their negations individually constitutes a necessary condition for either high or non-high PPEE. A configurational analysis of the antecedent conditions is therefore required to identify the multiple pathways associated with these two outcomes.

Table 8. Necessity analysis of individual conditions

	PPEE-Enhancing Configurations		Non-PPEE-Enhancing Configurations	
	Consistency	Coverage	Consistency	Coverage
a1	0.5206	0.4938	0.5899	0.5997
~a1	0.5780	0.5681	0.5020	0.5288
b1	0.4016	0.3959	0.6569	0.6941
~b1	0.6898	0.6523	0.4283	0.4341
c1	0.4828	0.4662	0.6063	0.6275
~c1	0.6142	0.5928	0.4843	0.5009
d1	0.4371	0.4088	0.6964	0.6981
~d1	0.6773	0.6755	0.4103	0.4386
e1	0.5015	0.4914	0.5752	0.6040
~e1	0.5959	0.5668	0.5157	0.5256

Note: a, healthcare expenditure share; b, urbanization rate; c, college students per 10,000 people; d, green coverage rate of built-up areas; e, per capita road area.

4.4.3 Analysis of configurational pathways for PPEE enhancement and non-enhancement

To assess the sufficiency of different condition configurations for PPEE improvement and non-improvement, a truth-table analysis is conducted. Given the sample size, the raw consistency threshold is set at 0.80 and the frequency threshold at 1, following Ragin (2009) [81]. In accordance with Waldkirch et al. (2021) [82], the proportional reduction in inconsistency (PRI) threshold is set at 0.60. As reported in Figure 4, the analysis identifies three configurational pathways to PPEE improvement and six pathways to non-improvement.

Based on configurational characteristics, PPEE-improvement pathways were classified into two types: S1–S2 represent a “resource adaptation pathway under low urbanization and limited green space provision”, while S3 represents a “road infrastructure compensation-driven pathway”. Non-improvement pathways were

categorized into three types: H1–H3 represent “high urbanization with insufficient green space transformation”, H4 and H6 represent “education–road resource constraints under high urbanization”, and H5 represents “a mismatch between education–road resource concentration and insufficient healthcare investment”. The overall consistency and coverage of the PPEE-improvement configurations were 0.802 and 0.511, respectively, compared with 0.786 and 0.532 for the non-improvement configurations, indicating good explanatory power for both configuration types.

The “resource constraint adaptation” pathway is characterized by low urbanization and limited green coverage in built-up areas. S1 further features the core absence of the number of college students per 10,000 people, whereas S2 is defined by the core absence of healthcare expenditure share and the peripheral absence of per capita road area. This pathway suggests that, under relatively constrained urban development and public resource conditions, efficient allocation and utilization of existing resources can still facilitate PPEE improvement. S1 exhibits the highest raw coverage (0.425), while S2 shows the highest consistency (0.874). Importantly, these findings reflect the synergistic effects of multiple conditions rather than implying that reducing healthcare investment or green space provision independently promotes PPEE.

The “road infrastructure compensation-driven” pathway is characterized by the core absence of low urbanization and limited green coverage in built-up areas, the core presence of high per capita road area, and the peripheral presence of a relatively high healthcare expenditure share. This pathway suggests that road infrastructure can partially compensate for deficiencies in urbanization and green space conditions by improving the spatial accessibility of sports, healthcare, and health services, thereby facilitating the conversion of public health resources into PPEE.

The “high urbanization with insufficient green space transformation” pathway (H1–H3) is characterized by high urbanization and relatively high green coverage in built-up areas. H1 is additionally associated with the peripheral absence of higher education resources, H2 with the core absence of healthcare investment, and H3 with

relatively high road infrastructure. This pathway indicates that advantages in urbanization, green space, and infrastructure do not necessarily translate into PPEE improvement, as insufficient human capital, healthcare investment, or resource coordination may constrain the conversion of inputs into efficiency gains. H3 has the highest raw coverage (0.339), representing the most extensive non-improvement pathway.

The “education–road resource constraints under high urbanization” pathway (H4 and H6) is characterized by the coexistence of high urbanization with deficiencies in higher education and road resources. H4 further exhibits the peripheral absence of healthcare investment, whereas H6 shows the core absence of green space provision despite relatively high healthcare investment. This pathway suggests that, without coordinated improvements in human capital, transportation infrastructure, and green space, increased healthcare investment alone cannot compensate for structural resource constraints.

The “mismatch between education–road resource concentration and insufficient healthcare investment” pathway (H5) is characterized by the core presence of higher education resources and per capita road area, the core absence of healthcare expenditure share, and relatively high green coverage in built-up areas. This configuration indicates that the benefits of education, transportation, and green space resources can only be translated into PPEE improvement when effectively coordinated with healthcare investment and health service systems.

Solutions and pathways for improving and non-improving PPEE.

Causal conditions	PPEE-Enhancement Configurations			Non-PPEE-Enhancement Configurations					
	S1	S2	S3	H1	H2	H3	H4	H5	H6
Share of Medical and Health Expenditure		⊗	●		⊗		⊗	⊗	●
Urbanization Rate	⊗	⊗	⊗	●	●	●	●		●
University Students per 10,000 Population	⊗			⊗			⊗	●	⊗
Green Coverage Rate of Built-up Areas (%)	⊗	⊗	⊗	●	●	●		●	⊗
Per Capita Road Area		⊗	●			●	⊗	●	⊗
Raw coverage	0.425	0.242	0.167	0.219	0.269	0.339	0.118	0.119	0.065
Unique coverage	0.170	0.039	0.035	0.034	0.060	0.115	0.037	0.006	0.016
Consistency	0.809	0.874	0.816	0.788	0.788	0.791	0.785	0.739	0.820
Solution coverage		0.511				0.532			
Solution consistency		0.802				0.786			

Note: ● indicates the presence of a core condition, ● represents the presence of a marginal condition, ⊗ signifies the absence of a core condition, ⊗ indicates the absence of a marginal condition, and a blank space implies that the presence or absence of the condition is irrelevant to the outcome.

Figure 4. Configurations and pathways leading to PPEE improvement and non-improvement.

4.4.4 Robustness Test for the fsQCA Analysis

Assessing the robustness of the results is an essential step in fsQCA. Following established practice, this study conducts a robustness test by varying the raw consistency threshold from 0.80 to 0.75 and 0.85 (Table 9). The adjustments produce no substantial changes in solution coverage or solution consistency. Therefore, the three pathways to PPEE improvement and six pathways to PPEE non-improvement identified from the five conditions demonstrate strong robustness and are applicable to the analysis of the 31 provinces in the study area.

Table 9. Robustness test results for the fsQCA analysis

	PPEE-Enhancing Configurations			Non-PPEE-Enhancing Configurations		
	0.75	0.80	0.85	0.75	0.80	0.85
Raw coverage	0.75	0.80	0.85	0.75	0.80	0.85
Solution coverage	0.511	0.511	0.511	0.532	0.532	0.532

Solution consistency	0.802	0.802	0.802	0.786	0.786	0.786
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5 Discussion

This study examines 31 provincial-level regions in China to investigate the spatiotemporal patterns and spatial spillover effects of PPEE. A multidimensional evaluation framework is developed by incorporating resource inputs, desirable outputs, and the obesity rate as an undesirable output to assess the dynamic evolution and spatial differentiation of PPEE. The direct and spatial spillover effects of multiple determinants are then estimated to clarify their influence and underlying mechanisms. Finally, fsQCA is employed to identify the configurational effects of these determinants and propose feasible pathways for improving PPEE.

5.1 Stage-specific fluctuations and regional differentiation patterns of PPEE

The estimated PPEE results indicate pronounced stage-specific fluctuations in China between 2014 and 2023, characterized by a short-term increase, a sustained decline, a temporary recovery, and a subsequent downturn, with no stable upward trend. Although previous studies have identified economic development, technological progress, and optimized resource allocation as key drivers of public sports service efficiency, input expansion may also generate resource redundancy and efficiency losses [51, 83]. At the provincial level, this study further finds that Hainan, Guizhou, Yunnan, Tibet, and Ningxia repeatedly recorded efficiency scores above 1, while Henan, Hubei, Guangdong, Sichuan, and several northwestern provinces reached the efficiency frontier in specific years. These provinces therefore demonstrated a strong capacity to allocate resources efficiently and convert them into health outcomes.

However, these periodic improvements did not alter the regional differentiation of PPEE. The western region recorded the highest mean efficiency, followed by

Northeast China, while the central and eastern regions exhibited relatively lower levels, forming a spatial pattern of “higher in the west and lower in the east”. This finding differs from Xu et al. (2024) [84], who reported that the eastern region led in the resource utilization efficiency of sports infrastructure, suggesting that advantages in resource provision do not necessarily translate into efficient health outcomes. The eastern region may be constrained by input redundancy and undesirable outputs such as obesity, whereas some western provinces achieve relatively high health outcomes with limited inputs. Therefore, without optimizing the input structure and strengthening the conversion of resources into health outcomes, regional resource advantages may not generate sustained improvements in PPEE.

5.2 Drivers of PPEE improvement from a GML perspective

The GML decomposition of PPEE in China shows that, although previous research has identified technological progress as a key driver of productivity growth in sports infrastructure and health services [84], this study further confirms the dominant role of technological change in promoting PPEE growth. In particular, advances in digital physical fitness monitoring, intelligent fitness services, and health-risk identification have enhanced the conversion of physical fitness resources into desirable outcomes. This finding is consistent with Ye and Tao (2023) [85], who identified technological change as a central driver of productivity growth in healthcare services. However, the efficiency change index increased relatively slowly and exhibited pronounced fluctuations, indicating persistent deficiencies in resource allocation, organizational management, and the application of technological innovations. This result aligns with Zhou et al. (2017) [86] and Sun et al. (2023) [87], who highlighted uneven resource allocation, input redundancy, and resource underutilization in the health service sector. Delayed efficiency catch-up may further widen PPEE disparities among regions with uneven technological development. Therefore, although technological progress provides a major impetus for improving PPEE, enhancing resource allocation and managerial efficiency remains essential for achieving sustained growth.

5.2 Direct effects of influencing factors on PPEE

Ray and Linden (2020) reported that increased public healthcare expenditure contributes to improved population health, longer life expectancy, and reduced mortality risk [88]. However, this study found that the share of healthcare expenditure has a significant negative effect on PPEE, which differs from previous findings. This discrepancy may be explained by the fact that increased healthcare spending is often concentrated in curative care and hospital operations, while investments in preventive services, health education, exercise promotion, weight management, and chronic disease prevention remain insufficient [89]. Guo et al. (2021) further demonstrated that the efficiency of provincial government healthcare expenditure in China still has substantial room for improvement, indicating that greater investment does not necessarily generate proportional health outcomes [90]. Therefore, when healthcare expenditure is not effectively transformed into preventive health services and integrated health–exercise interventions, a higher expenditure share may increase input costs without producing corresponding improvements in PPEE.

Previous studies have shown that urbanization can promote population health by improving infrastructure, healthcare accessibility, and socioeconomic conditions [91]. However, this study found that urbanization has a significant negative effect on PPEE, which may reflect its dual impacts on health efficiency. While urbanization enhances health service provision, it may also reduce physical activity and increase obesity risks through lifestyle transitions. Ng et al. (2009) found that rapid urbanization in China was closely associated with declines in occupational physical activity among adults [72]. Moreover, sedentary lifestyles and increased motorized transportation during urbanization may further restrict daily physical activity and contribute to obesity [92, 93]. Therefore, without parallel improvements in sports facilities, active transportation, and health promotion services, the resource advantages brought by urbanization may not be effectively translated into PPEE improvement.

Previous studies have shown that higher education can promote population health by enhancing health literacy and improving health behaviors [94, 95]. However,

this study found that the number of college students per 10,000 people has a significant negative effect on PPEE, possibly because this indicator mainly captures the regional concentration of higher education resources rather than their effective transformation into public health benefits. University-based sports and health resources primarily serve campus populations, with limited spillover to the wider community [96]. Moreover, insufficient physical activity and sedentary behaviors among college students suggest that higher education resource agglomeration does not necessarily translate into improved physical fitness outcomes [97]. Therefore, without effective conversion of educational advantages into public sports participation and public health services, higher educational resource concentration may not generate corresponding improvements in PPEE.

5.3 Spatial spillover effects of influencing factors on PPEE

Previous studies have shown that urbanization can promote the agglomeration of healthcare resources and improve health service accessibility [91, 98]. However, this study found a significant negative spatial spillover effect of urbanization on PPEE in neighboring regions, which may be attributed to the resource agglomeration effects associated with urbanization. Rapid urbanization drives the concentration of population, employment, and public services in core cities, increasing pressure on surrounding regions through the outflow of health resources and labor and exacerbating regional disparities in health resource allocation [99]. Meanwhile, urbanization-related lifestyle transitions may reduce physical activity levels. Monda et al. (2007) [100] and Ng et al. (2009) [72] found that rapid urbanization in China was closely associated with declines in occupational physical activity. Therefore, the combined effects of resource concentration in core cities and the diffusion of sedentary lifestyles may reduce the utilization efficiency of sports and health resources in neighboring regions, thereby constraining PPEE improvement.

This study found that per capita road area exerts a significant positive spatial spillover effect on PPEE in neighboring regions, consistent with previous evidence on the positive externalities of transport infrastructure. Yu et al. (2013) demonstrated that

transport infrastructure generates significant spatial spillovers in China, largely due to the strong regional connectivity of transport networks [101]. Further studies have shown that transport infrastructure can reduce spatial barriers, facilitate factor mobility, and promote public service sharing [102, 103]. Therefore, improved road networks may enhance regional accessibility, facilitate the cross-regional flow of sports, healthcare, and health service resources, and expand the coverage of high-quality health resources, thereby promoting PPEE improvement in neighboring regions.

5.4 Configurational pathways for PPEE improvement and non-improvement

Based on Ragin's (2008) [104] configurational theory, this study identified a "resource adaptation pathway under low urbanization and limited green space provision" that facilitates PPEE improvement. Both S1 and S2 are characterized by the core conditions of low urbanization and limited green coverage in built-up areas, accompanied by deficiencies in higher education resources or healthcare investment, respectively. This finding is consistent with Han and Zou (2024) [105], who emphasized that public sports service efficiency is shaped by multiple resource combinations and coordinated allocation. A possible explanation is that, in regions with relatively limited urban development and resource availability, lower service demand pressures may improve resource matching, allowing higher input-output efficiency through optimized allocation and utilization of existing resources [49]. Importantly, this pathway reflects the synergistic effects of multiple conditions rather than implying that reduced healthcare investment or green space provision independently promotes PPEE improvement.

The "road infrastructure compensation-driven" pathway further indicates that road infrastructure can promote PPEE improvement when other resource conditions are limited, consistent with previous findings that transport infrastructure enhances public service accessibility and resource allocation efficiency [106]. This may be attributed to the ability of well-developed road networks to reduce spatial barriers to

accessing sports, healthcare, and health services, expand the service coverage of public resources, and facilitate resource sharing, thereby improving the utilization efficiency of existing sports and health resources [107, 108].

The “high urbanization with insufficient green space transformation” pathway indicates that high urbanization and greater green space provision do not necessarily lead to PPEE improvement. Previous studies have shown that the health benefits of green spaces depend not only on their availability but also on accessibility, utilization, and social environmental conditions [109]. Moreover, health outcomes rely on the coordinated allocation of multiple resources, including education, healthcare, and environmental resources, as single-resource advantages may not be effectively transformed into health gains [110].

The “education–road resource constraints under high urbanization” pathway indicates that deficiencies in higher education and road infrastructure may hinder PPEE improvement in highly urbanized regions. Previous studies have shown that health system performance depends not only on financial investment but also on the allocation of skilled human resources and service accessibility [111, 112]. In addition, inadequate transportation conditions can increase spatial barriers to public service access and reduce the efficiency of health resource utilization [113].

The “mismatch between education – road resource concentration and insufficient healthcare investment” pathway indicates that abundant educational and road resources alone do not guarantee PPEE improvement. Previous studies have shown that health service accessibility is jointly influenced by healthcare resources, transportation conditions, and population demand [114]. This may be because higher education and transport infrastructure primarily provide supportive conditions, whereas healthcare investment constitutes a fundamental basis for health service provision [115, 116]. When healthcare resources are insufficient, the advantages of education and transportation may not be effectively transformed into physical fitness benefits.

5.5 Limitations and future directions

5.5.1 Limitations in the study scope

This study has several limitations. First, although the provincial-level analysis captures the macro-level differences and spatial associations of PPEE, it cannot fully identify heterogeneity across cities, urban–rural areas, or population groups within provinces. Second, due to limitations in statistical definitions, missing data, and interprovincial comparability, some indicators were estimated using interpolation or proxy measures, which may affect measurement accuracy. Third, the results of the Super-SBM, GML, and SDM models may be sensitive to indicator selection, model specifications, and spatial weight matrices. The fsQCA findings may also be influenced by calibration anchors, case frequency, and consistency thresholds, while the province–year case design does not fully account for temporal dependence and configurational evolution, requiring cautious causal interpretation. Finally, structural shocks arising from policy changes and reallocation of public health resources were not explicitly identified in this study.

5.5.2 Future research directions

To address these limitations, future research could refine the spatial scale from provinces to cities and counties to better capture regional heterogeneity in PPEE. Extending the study period would also help identify its dynamic evolution, stage characteristics, and spatial pattern changes. Moreover, future studies should incorporate additional external factors, such as air quality, climatic conditions, built environments, and accessibility of public sports facilities, using remote sensing, environmental monitoring, and geospatial data to explore their mechanisms. Furthermore, integrating behavioral and socioeconomic factors, including exercise habits, healthy lifestyles, population mobility, income levels, and policy implementation differences, with survey, interview, and individual-level data would facilitate a comprehensive “individual – environment – institution” framework to better understand how sports resource allocation, public health services, and individual behaviors jointly shape PPEE.

5.6 Policy implications and cross-regional collaborative governance pathways

5.6.1 Management implications

5.6.1 Promoting the transformation of physical fitness and health governance from input expansion to efficiency improvement

PPEE remains relatively low nationwide, and some economically developed provinces with high levels of resource input still exhibit unsatisfactory efficiency, indicating that greater investment does not necessarily translate into better physical fitness and health outcomes. Local governments should therefore shift their focus from expanding funding, facilities, and projects toward improving resource utilization and health outcomes. Greater coordination is needed across sports, healthcare, education, and community services to promote the shared use of public sports venues, school sports facilities, and primary health facilities, while reducing duplication, idle resources, and administrative fragmentation. In addition, improvements in residents' physical fitness, facility utilization, and service coverage should be incorporated into public expenditure performance evaluation to strengthen the conversion of public investment into PPEE gains.

5.6.2 Promoting synergistic improvements in technological progress and management efficiency

The GML decomposition results show that technological progress has contributed to PPEE improvement in certain periods, but insufficient efficiency catch-up may constrain its effectiveness. Therefore, technological innovation should not be measured solely by patent growth or equipment expansion; greater emphasis should be placed on its practical application in physical fitness assessment, exercise interventions, public fitness services, and health management. Promoting the extension of digital fitness monitoring platforms, smart fitness facilities, and exercise health services to grassroots levels, while strengthening professional training, equipment maintenance, and data utilization capacity, can facilitate the transformation

of technological advances into improved public service efficiency and population physical fitness.

5.6.3 Implementing differentiated governance based on regional disparities

PPEE in China exhibits clear regional disparities, with different areas requiring distinct combinations of conditions for efficiency improvement. Therefore, a uniform governance model should be avoided. In the eastern region, where economic development is relatively advanced but efficiency remains suboptimal, priorities should include reducing resource redundancy, improving facility utilization, and enhancing input–output conversion through more targeted services. For western and other high-efficiency regions, the focus should be on maintaining efficient resource allocation while improving service accessibility for remote areas and grassroots populations. In the central and northeastern regions, efforts should emphasize the upgrading of existing sports and health facilities, strengthening grassroots professional capacity, and promoting coordinated public service provision to develop region-specific pathways for PPEE improvement.

5.6.4 Enhancing cross-regional collaboration and resource optimization

Given the significant negative spatial spillover effect of urbanization and the positive spillover effect of road infrastructure, greater emphasis should be placed on regional coordination in public resource allocation. On the one hand, excessive concentration of high-quality resources in core cities during urbanization should be avoided to reduce the adverse effects of resource siphoning and spatial mismatch on neighboring regions' PPEE. On the other hand, regional transport networks should be continuously improved to enhance cross-regional accessibility and sharing of sports, healthcare, and health services. Strengthening collaboration among neighboring regions in facility planning, talent allocation, and public service provision can promote a shift from isolated resource allocation toward integrated regional governance, thereby facilitating coordinated improvements in PPEE.

6 Conclusion

This study employed the Super-SBM, GML index, SDM, and fsQCA to investigate the spatiotemporal evolution, spatial effects, and configurational pathways of PPEE across 31 provincial-level regions in China from 2014 to 2023. The results indicate that China's PPEE remains relatively low with significant regional disparities, and its improvement is primarily driven by technological progress. Spatial analysis shows that healthcare expenditure share, urbanization rate, and college students per 10,000 people negatively affect local PPEE; urbanization generates negative spatial spillovers, whereas road infrastructure produces positive spillovers. The fsQCA results reveal causal complexity and asymmetry, with PPEE improvement arising mainly from resource adaptation and road infrastructure compensation pathways, while non-improvement is associated with insufficient resource transformation, structural constraints, and resource mismatches. These findings suggest that PPEE is shaped by the synergistic configuration of multiple resources rather than individual factors. Therefore, future policies should emphasize efficient resource allocation, cross-sector coordination, region-specific governance, and interregional collaboration to promote PPEE improvement and balanced regional development.

Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Informed Consent

This article does not contain any studies with human participants performed by any of the authors.

Data Availability Statement

The datasets used in this study are available from the corresponding author upon reasonable request. The supplementary files include the datasets, variable definitions, data processing procedures, and Stata codes used for the analyses.

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