Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-025-05445-z OPEN

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Advancing urban sustainability assessment: a novel DEA-based framework for multidimensional analysis in Chinese cities

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Many cities worldwide grapple with social challenges due to uneven socio-economic development, jeopardizing their long-term sustainability. To address these issues—especially in developing countries—this study introduces an extended sustainability framework that tackles both infrastructure disparities and the need for quality socio-economic progress. This comprehensive framework incorporates three dimensions—economy-environment, infrastructure construction, and social development—each characterized by distinct internal structures. To capture the complex interactions among these dimensions, we develop a novel methodological framework: the DEA-based Benefit of the Doubt (BoD) model. This model assesses the efficiency of the extended system across diverse structural configurations. Additionally, our framework integrates relative weight indexes, coupling-related indicators, and the BP-DEMATEL model. Through an empirical focus on Chinese cities, our findings reveal an upward trend in China's overall sustainability efficiency, albeit with considerable variability among cities. Specifically, overall efficiency has surged by 38.61%, with the social development dimension's efficiency escalating by 40.19%. Although continuous improvements are observed in coupling-related indicators, certain cities remain challenged in achieving synchronized growth across all dimensions. Notably, the economy-environment dimension emerges as a pivotal driving factor, while infrastructure construction and social development dimensions are identified as crucial for long-term urban sustainability. This study offers policy-relevant insights to help governments optimize urban sustainability strategies, ensuring more tailored, data-driven, and inclusive urban development.

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Introduction

Globally, numerous cities are confronting a spectrum of social challenges—such as disparities in educational opportunities, and employment hurdles—stemming from uneven development across diverse socio-economic domains, thereby posing significant threats to long-term sustainability. To address this, the Sustainable Development Goals, introduced by the United Nations in 2015, emphasize the importance of achieving a harmonious balance among social, economic, and environmental dimensions. Within academic discourse, the exploration of city sustainable development has seen a significant expansion in scope and depth. Initially, sustainability primarily focused on economic and environmental concerns. However, attention has increasingly shifted towards infrastructure construction and social development, given the pronounced global disparities in these areas. The persistence of such disparities undermines global efforts to narrow sustainability gaps worldwide (Karaca et al. 2015; Laali et al. 2022). The interplay among economic growth, environmental issues, infrastructure construction, and social development highlights the need to understand and evaluate complex dynamics within urban sustainability system, identifying key drivers to enhance their efficiency. Some studies focus on economic performance, energy efficiency, infrastructure resilience, governance quality, and innovation capabilities (Wang et al. 2024; Wu and Chang, 2024). Additionally, some studies have explored urban ecosystem development through the lens of resource utilization and environmental pollution (Razia and Abu Bakar Ah, 2023; Li et al. 2024). However, a formidable challenge in this endeavor is accurately disentangling the effects of different dimensions on an urban sustainability system and thus overcoming barriers to its improvement.

To effectively assess an urban sustainability system, two primary methodological challenges must be addressed. Firstly, there is an urgent need for a unified methodological framework capable of evaluating the efficiency of an extended sustainability system that encompasses multiple internal dimensions. Secondly, accurately identifying the key driving forces behind sustainability remains crucial.

In the research field of efficiency evaluation, the data envelopment analysis (DEA) model has received widespread reputation for its ability to assess the efficiency of production processes, accounting for both desirable and undesirable outputs. Moreover, the Benefit of the Doubt (BoD) model provides flexibility in handling production processes that involve either outputs or inputs exclusively. However, neither the DEA model nor the BoD model is capable of handling production processes with varying structures across different production stages. To address this challenge, this study proposes a novel DEA-based BoD model, which integrates dimensions with varying structures into a unified framework, as detailed in the section "Methods". Moreover, traditional DEA model faces the deficiency of the possible occurrence of multiple projections and reference sets, resulting in the issue of multiple optimal weights for its optimal solution (Sueyoshi and Sekitani, 2007). To address this deficiency, this study adopts strong complementary slackness conditions (Sueyoshi and Goto, 2012; Chen et al. 2015).

Methodologically, the identification of the key driving forces has been approached through various methodologies, including regression analysis (Liu et al. 2019; Yu and Zhao, 2020; Li et al. 2023), variable dimension reduction (Upadhyay and Chauhan, 2022; Popkova et al. 2022; Luo et al. 2023), correlation analysis (Sarkhosh-Sara et al. 2020), and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) model (Kumar et al. 2023). Notably, DEMATEL model stands out for its ability to reliably identify influential dimensions, even with limited data (Gani et al. 2022). However, the application of DEMATEL indispensably requires the utilization of a direct relation matrix. In the traditional approach, the direct relation matrix is evaluated through expert scores or questionnaires. This results in several limitations, such as challenging implementation, subjectivity, and time consumption. To address this limitation, our study employs the Back Propagation (BP)-DEMATEL model for weight assignment, drawing on methods proposed by Cui et al. (2013) and Li et al. (2020).

Empirically, this study examines urbanization challenges faced by China's cities and their efforts to foster sustainable urban development. To this end, this study utilizes a sample of 261 Chinese cities from 2009 to 2018 for an empirical analysis within our new framework. The study evaluates the efficiency of city-level sustainability system across various dimensions. Our findings identify key inefficiencies and the underlying driving forces influencing urban sustainability, thereby providing policymakers with actionable insights for crafting targeted interventions to bolster urban sustainability.

The main contributions of this paper are twofold. Methodologically, we introduce a novel framework that encompasses a novel DEA-based BoD model for efficiency analysis, relative weight indexes to clarify dimension priority, coupling-related indexes to assess cross-dimensional coordination, and a BP-DEMATEL model to identify the driving and characteristic dimensions of the sustainability system. Notably, our novel DEA-based BoD model is designed to accommodate varying structures within the sustainability system. Importantly, our extended sustainability system encompasses economy-environment, infrastructure construction, and social development dimensions, with a focus on human development quality.

Empirically, we shed light on China's environmental challenges and regional economic disparities, underscoring the critical need for balanced infrastructure and social development to achieve sustainable growth. Our findings provide policymakers with actionable insights, guiding targeted interventions to foster sustainable city development across multiple dimensions.

literature review

This study introduces a novel methodological framework for assessing the efficiency of urban sustainability system in China. Our framework integrates DEA-based BoD model, relative weight indexes, coupling-related indexes, and the BP-DEMATEL model. Consequently, two groups of studies are closely related to this research.

The first research group comprises recent studies on DEA (or BoD) with a focus on sustainability, as presented in Table 1. It offers two intriguing insights. Firstly, sustainability is characterized by multiple dimensions, with the majority of studies concentrating on the economy, environment, and society aspects. Specifically, economy indicators typically include capital, electricity, labor, and GDP (Yao et al. 2022). Environment indicators encompass solid waste, sulfur dioxide, and wastewater (Li et al. 2023; Xu et al. 2024). Social indicators comprise education expenditure and hospital beds (Shi et al. 2022). Additionally, "doctors" is selected as an output indicator in social dimension (Pereira et al. 2021). Secondly, the existing studies have employed DEA model, network DEA model, and BoD model to measuring the efficiency of sustainability system. Specifically, the DEA model is applicable to single-stage systems characterized by both input and output indicators (Zhao et al. 2019). The network DEA model is suitable for sustainability systems comprising two or more stages (Shi et al. 2022). Meanwhile, the BoD model has advantage in systems that solely feature output indicators (Martínez et al. 2020; Magrini and Giambona, 2022).

The second research group is related to studies that employ the DEMATEL model, as presented in Table 2. In the existing literature,

Table 1 Recent DEA/BoD studies on sustainable development.

Article	Coverage	Feature of DEA or BoD	Dimension	Assisting method	Coupling index	DEMATEL	Relative weight analysis
Wu and Chang (2024)	38 major Chinese cities, 2015–2019	Network SBM DEA	Economy, environment and society	Kruskal–Wallis test	\	\	\
Xu et al. (2024)	30 provincial cities, China, 2009	Super-efficiency DEA	Economy and environment	\	\	\	\
Chen et al. (2023)	114 resource-based cities, China, 2003–2016	Windows-Bootstrap-DEA	Environment, resource and economy	Spatial autocorrelation, conditional probability density estimation, Tobit	\	\	\
Li et al. (2023)	59 cities, Yellow River Basin, China, 2007–2019,	SBM	Economy, society, environment and technology	Tobit, time-lag analysis, GTWR	\	\	\
Kutty et al. (2022)	35 cities, Europe, 2015–2020	Double frontier SBM, bounded-DEA	Energy and environmental resources, governance and institutions, economic dynamism, social cohesion and solidarity, climate change, safety and security	MPI, quartile clustering method	\	\	\
Gao et al. (2022)	28 cities, China, 2012–2019	Two-stage correlation DEA	Land, economy, environment and society	Perpetual inventory method, global Moran's index	\	\	\
Wang et al. (2022)	287 cities, China, 1985–2015	CCR	Resource, society, economy and environment	\	\	\	\
Shi et al. (2022)	33 cities, China, 2014–2018	Parallel two-stage SBM dynamic model	Society, economy, ecology and quality of life	Kernel density analysis	\	\	\
Liu et al. (2022)	8 megacities, China, 2007–2016	SBM	Economy, environment and society	Shannon-Wiener formula, emergy ecological intensity index	\	\	\
Yao et al. (2022)	16 cities, Songnen-Sanjiang Plain, China, 2006–2019	SBM	Economy, society, environment and ecology	\	\	\	\
Li et al. (2022)	31 provinces, China, 2005–2019	CCR	Water resource, society, economy and ecology	Gini coefficient, WEF model, Euclidean distance approach, sensitivity analysis	\	\	\
Magrini and Giambona (2022)	27 EU countries plus the United Kingdom, 2004–2020	BoD	Economy, environment and society	Cointegration Analysis	\	\	\

Table 1 (continued)

Article	Coverage	Feature of DEA or BoD	Dimension	Assisting method	Coupling index	DEMATEL	Relative weight analysis
López-Penabad et al. (2022)	114 rural municipalities, Galicia, 2021	BoD	Economy, environment, demography and society	Truncated regression	\	\	\
de Araújo et al. (2021)	41 municipalities, Brazil, 2014–2016	BCC	Resource consumption, transportation and environment	Tobit	\	\	\
Yao et al. (2021)	28 cities, Russia, 2010–2019	CCR, SBM, EBM	Economy and environment	\	\	\	\
Wang et al. (2021)	43 cities, Yellow River Basin, 2007–2017	Super-efficiency SBM	Economy and environment	Spatial autocorrelation	\	\	\
Long (2021)	35 cities, China, 2011–2015	Super-efficiency SBM	Economy, environment, education and health	Malmquist-Luenberger index	\	\	\
An et al. (2021)	34 towns, Xiangjiang River Basin, China, 2016	CCR	Economy and environment	Cross-efficiency	\	\	\
Pereira et al. (2021)	181 countries, 2016–2020	DDF BoD	Health	Convergence	\	\	\
Cui et al. (2021)	60 cities, China, 2013–2017	Dynamic DEA	Economy and environment	Factor analysis method	\	\	\
Yu and Zhao (2020)	21 Cities, Guangdong Province, China, 2008–2016	Input-oriented DEA	Economy, resources and environment	MPI, generalized method of moments, stability test	\	\	\
Zhang (2020)	26 cities, Yangtze River Delta, China, 2005–2016	DEA	Economy, industrial structure, technology and environment	Moran's index, spatial Durbin model, partial differential matrix	\	\	\
Sarkhosh-Sara et al. (2020)	97 countries, 2011	Double frontier DEA	Economy, environment and country income class	Correlation coefficients	\	\	\
Boussemart et al. (2020)	20 OECD countries, 2005–2014	DDF DEA	Economy, environment and society	\	\	\	\
Martínez et al. (2020)	202 municipalities, Spain	BoD	Economy, environment and society	\	\	\	\
Zhu et al. (2019)	35 cities, China, 2007–2015	Super efficiency SBM	Economy, environment, society, infrastructure and land	PLS-SEM model, average variance extracted test, convergent validity	\	\	\
Zhao et al. (2019)	30 cities, China, 2011–2013	Noncooperation DEA, cooperation DEA	Economy, environment and society	Bilevel programming problem	\	\	\
Liu et al. (2019)	239 cities, China	DDF DEA	Economy and environment	Spearman ranking correlation, Tobit	\	\	\

BCC Banker–Charnes–Cooper model, *BoD* Benefit of the Doubt, *CCR* Charnes–Cooper–Rhodes model. DDF: directional distance function, *DEA* data envelopment analysis, *EBM* epsilon-based measure, *EU* European Union, *GTWR* geographically and temporally weighted regression model, *MPI* Malmquist productivity index, *OLS* ordinary least squares, *PLS-SEM* partial least-squares structural equation modeling, *SBM* slacks-based measure model, *SFA* stochastic frontier analysis, *WEF* water ecological footprint model.

Table 2 Recent DEMATEL studies.

Article	Coverage	Research field	Feature of DEMATEL	Assisting method	Coupling index	BoD	DEA	Relative weight analysis
Liu et al. (2023)	110 cities, China, 2014-2018	Urban innovation ecosystem	BP DEMATEL	NK model	\	\	\	\
Bao et al. (2023)	5 mature coal cities, China, 2019	Environmental carrying capacity	BP DEMATEL	Normal cloud model	\	\	\	\
Kumar et al. (2023)	5 food organizations, India	Food	Grey DEMATEL	ISM	\	\	\	\
Wu et al. (2022)	7 academic departments, a university	Education	DEMATEL	TODIM method, sensitivity analysis, cross-efficiency	\	\	√	\
Lu et al. (2022)	30 provinces, China, 2007-2017	Energy poverty	Fuzzy DEMATEL	Clustering analysis	\	\	√	\
Wang et al. (2022)	125 cities, China, 2011, 2013, 2015, 2018	Health	FSM-DEMATEL	Grey entropy weight	\	\	\	\
Ren et al. (2022)	Taishan Mountain, China	Mountain	BP DEMATEL	\	\	\	\	\
Liu et al. (2022)	4 provinces, China	Sustainable supply chain	DEMATEL	ANP, system collaboration model	\	\	\	\
Altuntas and Gok (2021)	12 regions, Turkey	Health	DEMATEL	\	\	\	\	\
Chen and Chen (2021)	11 provinces or municipalities, China, 2008-2017	Water–energy–food coordination	DEMATEL	CRITIC, entropy weight, GTCW, symbiotic Index	\	\	\	\
El-Garaihy (2021)	20 supply chain, Saudi Arabia, 2018-2019	Supply chain	DEMATEL	\	\	\	√	\
Kilic and Yalcin (2021)	5 municipalities, Asia	Environmental sustainability	Neutrosophic DEMATEL	TOPSIS	\	\	\	\
Ghosh et al. (2021)	Kolkata Metropolitan Area, India, 2001-2011	Urban ecological security	DEMATEL	ANP, cellular automata-Markov	\	\	\	\
de Campos et al. (2021)	10 municipal pharmacies, Brazil	Health	Grey DEMATEL	\	\	\	\	\
Qin et al. (2020)	Jinan, China, 2017	Urban shrinkage risk	BP DEMATEL	Entropy weight	\	\	\	\
Li et al. (2020)	Pearl River Delta urban agglomeration, China	Regional sustainability	BP DEMATEL	Coordination degree model	\	\	\	\
Yazdani et al. (2020)	Alboraya town, Valencia Province, Spain	Sustainable agricultural supply chain	Fuzzy DEMATEL	Quality function deployment	\	\	\	\
Jiang et al. (2020)	A hospital, Shanghai, China	Health	linguistic Z-DEMATEL	Sensitivity analysis	\	\	\	\
Wang et al. (2019)	A hotel, China	Energy	Interval DEMATEL	Interval VIKOR method	\	\	\	\

ANP analytic network process, *BP* back propagation, *CRITIC* criteria importance through intercriteria correlation, *DEMATEL* Decision-making Trial and Evaluation Laboratory, *FSM* fuzzy synthetic method, *ISM* interpretive structural modeling, *TOPSIS* technique for order of preference by similarity to ideal solution.

the DEMATEL model is utilized to perform causal analysis of the different dimensions in a system (Kilic and Yalcin, 2021; Wang et al. 2022). Ghosh et al. (2021) used the DEMATEL model to assess the direct relationship among the factors and identified the factors that play an important role in maintaining urban ecological security. Chen and Chen (2021) used BP-DEMATEL to assess symbiosis coordination of water–energy–food system and found that the energy-related indicators have a greater influence on the symbiotic development of the system. Liu et al. (2023) constructed an urban innovation ecosystem containing five subsystems. On this basis, the optimal evolution path of the Beijing innovation ecosystem was identified by the BP-DEMATEL model. However, no study integrates the dimensional efficiency of the BoD model with the BP DEMATEL model. Methodologically, the DEMATEL model mainly determines the direct relationship matrix required by a questionnaire survey or expert scoring. In contrast, the BP-DEMATEL model can avoid the problem of subjectivity by assigning weights through the back-propagation (BP) neural network method. (Li et al. 2020).

This study fully recognizes the foundational contributions of prior research while extending the existing literature through three key contributions. First, it advances theoretical understanding by systematically examining the sustainability system and elucidating the complex interrelationships among its three constituent dimensions. Second, it proposes an innovative methodological framework that integrates BP-DEMATEL into the DEA-based BoD model, with detailed conceptualization and implementation presented in the section "Methods". Third, the empirical findings provide actionable policy implications, enabling policymakers to formulate targeted strategies for enhancing urban sustainability and mitigating intercity efficiency disparities. Methodologically, the study establishes a "best practice" frontier using multiple decision-making units (DMUs) (Cooper et al. 2011), against which the relative efficiency of individual DMUs is rigorously assessed. Building on Kang et al. (2022), the concept of "efficiency gaps" is operationalized to quantitatively measure performance discrepancies among DMUs, thereby offering a systematic approach to identifying inefficiencies and potential areas for improvement in urban sustainability governance.

Methods

This study develops a novel methodological framework. The framework contains four types of academic efforts: (1) a new type of DEA-based BoD model for efficiency analysis; (2) relative weight indexes for priority analysis; (3) coupling related analysis to measure the association degree among dimensions; and (4) the BP-DEMATEL model for identifying driving and characteristic dimensions.

The three-division structure with assembly conversion. This study proposes a new network structure of sustainability system. This system contains three dimensions (or divisions). The dimensions entail economy–environment dimension, infrastructure construction dimension and social development dimension, as demonstrated in Fig. 1.

Specifically, the economy–environment dimension transforms inputs (x^1) into desirable outputs (y^1) and undesirable outputs (b^1). Here, the superscripts 1–3 represent three dimensions. For the infrastructure construction dimension, this study considers three types of desirable outputs (y^2). The social development dimension entails three aspects (i.e., education, health and culture). For the education dimension, two inputs($x^{3-\mathrm{e}}$) are transformed to produce one desirable output ($y^{3-\mathrm{e}}$). By comparison, health and culture dimensions solely produce desirable outputs ($y^{3-\mathrm{hea}}$, $y^{3-\mathrm{cul}}$). Here, the superscripts denote the three aspects (e: education, hea: health and cul: culture).

Regarding the indicators for the infrastructure construction dimension, Dong et al. (2018) emphasize the importance of the water infrastructure system in sustainability. Following Dong et al. (2018) and considering data accessibility, this study adopts drainage pipelines as an indicator. Li et al. (2023) suggest using green space area as a proxy for environmental enhancement. Building on this, green coverage is incorporated as an indicator for the infrastructure construction dimension in this study. Furthermore, Gao et al. (2022) propose road area per capita as an important aspect of sustainability. Accordingly, this study employs road area as an indicator.

In the education aspect, Zhu et al. (2019) identify three key indicators: the average number of primary and middle school teachers, the share of education expenditure in total financial expenditure, and the number of college students per 10,000 people. Drawing upon this framework, this study adopts "number of education employees" and "education expenditure" as input indicators, and "students" as an output indicator, in alignment with Zhu et al. (2019). Additionally, "graduates" or "employment rate" can also serve as reasonable output indicators, as they reflect the effectiveness of the education system. However, considering that the focus of this study is to analyze the relationship between educational input resources and the number of students. In this regard, "students" provides a more direct and relevant comparison with the input indicators, making it an appropriate output indicator in this study.

As for indicators in the health aspect, the number of hospital beds is used as an output indicator in the urban social subsystem (Shi et al. 2022). In Li et al. (2023), the number of medical beds per 10,000 people is a desirable output in the social welfare aspect. Additionally, the density of medical doctors per 10,000 population is an output indicator for the health aspect (Pereira et al. 2021). Based on this, "doctors" and "beds" are used as output indicators in this study. In the cultural aspect, Zhu et al. (2019) employ the number of public libraries per 10,000 people as the sole indicator. Given data availability constraints, this study adopts the public library collections as the primary output measure.

DEA model, BoD model and DEA-based BoD model. This study employs DEA models to evaluate dimensions with input–output structures, BoD models for dimensions with output-only structures, and a DEA-based BoD model to address the unified sustainability system with varying-structure dimensions.

The DEA model without undesirable output. As for the education aspect, each DMU (j) transforms various inputs (x) into desirable outputs (y). To evaluate this transformation process, this study utilizes an enhanced directional distance function approach to calculate the efficiency scores, drawing upon the framework established by Chen et al. (2015). The model is formulated as follows:

$$
\begin{aligned}
&\text{Maximize } \tfrac{1}{2}\left(\tfrac{1}{H}\sum_{h=1}^{H}\beta_{hk\tau}^{y^{3-e}}+\tfrac{1}{I}\sum_{i=1}^{I}\beta_{ik\tau}^{x^{3-e}}\right)\\
&s.t.\ \sum_{t=1}^{T}\sum_{j=1}^{J}\lambda_{jt}x_{ijt}^{3-\mathrm{e}}\le(1-\beta_{ik\tau}^{x^{3-e}})x_{ik\tau}^{3-\mathrm{e}}(i=1,\ldots,\mathrm{I}),\\
&\sum_{t=1}^{T}\sum_{j=1}^{J}\lambda_{jt}y_{hjt}^{3-\mathrm{e}}\ge(1+\beta_{hk\tau}^{y^{3-e}})y_{hk\tau}^{3-\mathrm{e}}(h=1,\ldots,H),\\
&\sum_{t=1}^{T}\sum_{j=1}^{J}\lambda_{jt}=1,\\
&\lambda_{jt}\ge0,\beta_{hk\tau}^{y^{3-e}}\ge0,\beta_{ik\tau}^{x^{3-e}}\ge0.
\end{aligned}
\tag{1}
$$

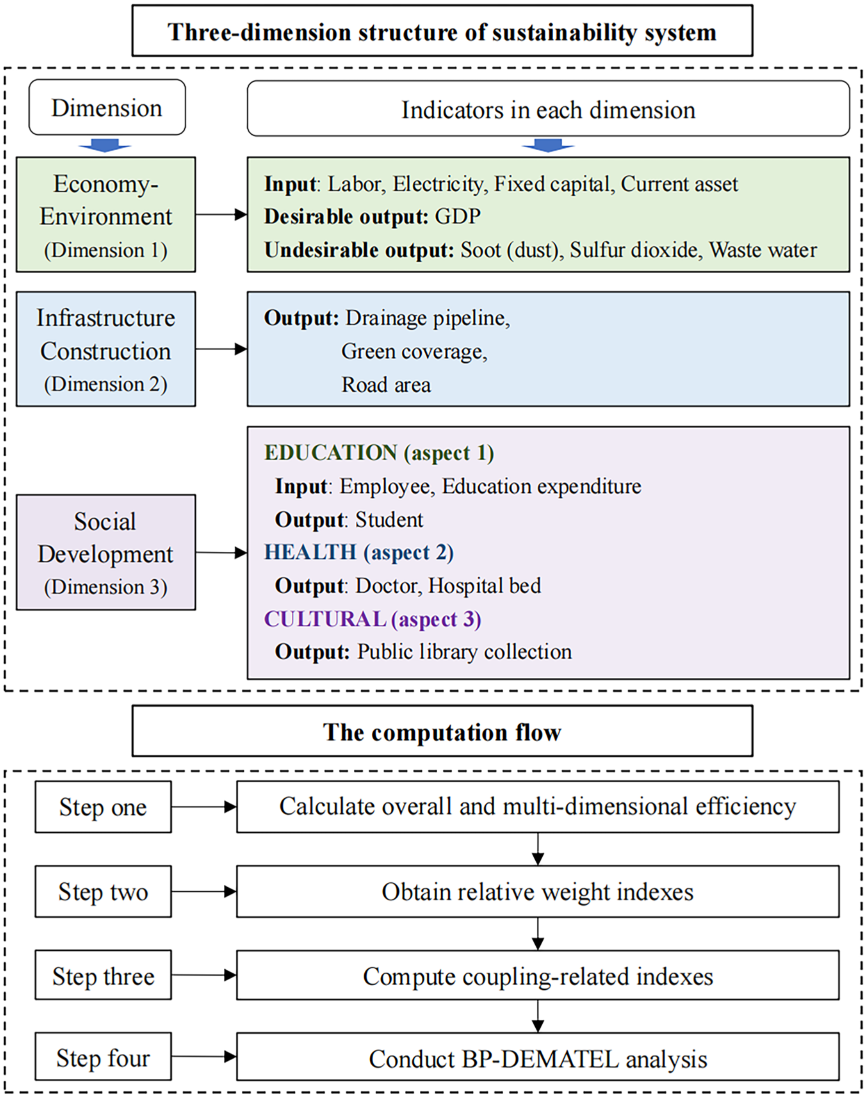

Fig. 1 The structure of the sustainability system and computation flow.

Here, λ denotes "intensive" or "structural" variables, functioning as links between inputs and outputs. β represents the largest possible adjustment ratio of various inputs and desirable outputs.

In Model (1), the first two constraints ensure that the DMU to be evaluated is located within or below the efficiency frontier. The third constraint means that Model (1) adopts the assumption of variable returns to scale.

After solving Model (1), the efficiency scores can be calculated by the following equation:

$$ES_{k\tau}^{3-edu} = \frac{1 - \frac{1}{I}\sum_{i=1}^{I} \beta_{ik\tau}^{x^{3-e^*}}}{1 + \frac{1}{H}\sum_{h=1}^{H} \beta_{hk\tau}^{y^{3-e^*}}}. \tag{2}$$

The DEA model with undesirable outputs. As for the economy–environment dimension, each DMU transforms various inputs (x) into desirable outputs (y) along with undesirable outputs (b). To deal with the occurrence of undesirable outputs, this study adopts an enhanced Russell-based measure based on the directional distance function approach after referring to Chen et al. (2015). The formula is shown as follows:

$$\begin{aligned}
&Maximize\ \frac{1}{2}\left(\frac{1}{H}\sum_{h=1}^{H}\beta_{hk\tau}^{y^1} + \frac{1}{L}\sum_{l=1}^{L}\beta_{lk\tau}^{b^1}\right)\\
&s.t. \sum_{t=1}^{T}\sum_{j=1}^{J}(\lambda_{jt}+\mu_{jt})x_{ijt}^1 \le x_{ik\tau}^1 (i=1,\ldots,\mathrm{I}),\\
&\sum_{t=1}^{T}\sum_{j=1}^{J}\lambda_{jt}y_{hjt}^1 \ge (1+\beta_{hk\tau}^{y^1})y_{hk\tau}^1 (h=1,\ldots,\mathrm{H}),\\
&\sum_{t=1}^{T}\sum_{j=1}^{J}\lambda_{jt}b_{ljt}^1 = (1-\beta_{lk\tau}^{b^1})b_{lk\tau}^1 (l=1,\ldots,\mathrm{L}),\\
&\sum_{t=1}^{T}\sum_{j=1}^{J}(\lambda_{jt}+\mu_{jt}) = 1,\\
&\lambda_{jt}\ge 0, \mu_{jt}\ge 0, \beta_{hk\tau}^{y^1}\ge 0, \beta_{lk\tau}^{b^1}\ge 0.
\end{aligned} \tag{3}$$

After solving Model (3), the efficiency scores can be obtained as follows:

$$ES_{k\tau}^{1-ee} = \frac{1 - \frac{1}{L}\sum_{l=1}^{L}\beta_{lk\tau}^{b^{1^*}}}{1 + \frac{1}{H}\sum_{h=1}^{H}\beta_{hk\tau}^{y^{1^*}}}. \tag{4}$$

The DEA-based BoD model. After referring to Chen et al. (2015) and Sahoo et al. (2017), this study proposes a new type of DEA-based BoD model. Our model has the following formulation:

$$
\begin{aligned}
&\theta_{k\tau} = Maximize \tfrac{1}{H}\left[\sum_{c=1}^{C}\sum_{h\in H^c}(\beta_{hk\tau}^{y^c}+\beta_{hk\tau}^{ES^c})\right]\\
&s.t.\ \sum_{t=1}^{T}\sum_{j=1}^{J}\lambda_{jt}ES_{hjt}^{c} \geq (1+\beta_{hk\tau}^{ES^c})ES_{hk\tau}^{c}(h\in H^c; c=1-ee, 3-edu),\\
&\sum_{t=1}^{T}\sum_{j=1}^{J}\lambda_{jt}y_{hjt}^{c} \geq (1+\beta_{hk\tau}^{y^c})y_{hk\tau}^{c}(h\in H^c; c=2, 3-hea, 3-cul),\\
&\sum_{t=1}^{T}\sum_{j=1}^{J}\lambda_{jt} = 1,\\
&\lambda_{jt}\geq 0, \beta_{hk\tau}^{y^c}\geq 0, \beta_{hk\tau}^{ES^c}\geq 0.
\end{aligned}
\tag{5}
$$

The dual of Model (5) is written as follows:

$$
\begin{aligned}
&\text{Minimize}\begin{pmatrix} -\sum_{h=1}^{H^2}u_h^2y_{hk\tau}^2-\sum_{h=H^2+1}^{H^{3-hea}}u_h^{3-hea}y_{hk\tau}^{3-hea}-\sum_{h=H^{3-hea}+1}^{H^{3-cul}}u_h^{3-cul}y_{hk\tau}^{3-cul}\\ -\sum_{h=H^{3-cul}+1}^{H^{1-ee}}u_h^{1-ee}ES_{hk\tau}^{1-ee}-\sum_{h=H^{1-ee}+1}^{H^{3-edu}}u_h^{3-edu}ES_{hk\tau}^{3-edu}+\sigma\end{pmatrix}\\
&\text{s.t.}\begin{pmatrix} -\sum_{h=1}^{H^2}u_h^2y_{hjt}^2-\sum_{h=H^2+1}^{H^{3-hea}}u_h^{3-hea}y_{hjt}^{3-hea}-\sum_{h=H^{3-hea}+1}^{H^{3-cul}}u_h^{3-cul}y_{hjt}^{3-cul}\\ -\sum_{h=H^{3-cul}+1}^{H^{1-ee}}u_h^{1-ee}ES_{hjt}^{1-ee}-\sum_{h=H^{1-ee}+1}^{H^{3-edu}}u_h^{3-edu}ES_{hjt}^{3-edu}+\sigma\end{pmatrix}\geq 0\begin{pmatrix} j=1,\ldots,J;\\ t=1,\ldots,T\end{pmatrix},\\
&u_h^{1-ee}ES_{hk\tau}^{1-ee} \geq 1/H,\\
&u_h^2y_{hk\tau}^2 \geq 1/H,\\
&u_h^{3-edu}ES_{hk\tau}^{3-edu} \geq 1/H,\\
&u_h^{3-hea}y_{hk\tau}^{3-hea} \geq 1/H,\\
&u_h^{3-cul}y_{hk\tau}^{3-cul} \geq 1/H,\\
&u\geq 0.
\end{aligned}
\tag{6}
$$

After solving Model (5) or Model (6), this study obtains the overall efficiency scores (CI) by Eq. (7).

$$
CI_{k\tau}^{o} = \frac{1}{1+\theta_{k\tau}^{*}}.
\tag{7}
$$

Meanwhile, the efficiency scores of three dimensions (i.e., EE: economy–environment, IC: infrastructure construction, SD: social development) can be computed in the following manner.

$$
\begin{aligned}
CI^{EE} &= \frac{1}{1+\frac{1}{H^1}\sum_{h\in H^1}\beta_{hk\tau}^{ES^{1-ee}}},\\
CI^{IC} &= \frac{1}{1+\frac{1}{H^2}\sum_{h\in H^2}\beta_{hk\tau}^{y^2}},\\
CI^{SD} &= \frac{1}{\left(1+\frac{\left(\sum_{h\in H^{3-edu}}\beta_{hk\tau}^{ES^{3-edu}}+\sum_{h\in H^{3-hea}}\beta_{hk\tau}^{y^{3-hea}}+\sum_{h\in H^{3-cul}}\beta_{hk\tau}^{y^{3-cul}}\right)}{(H^{3-edu}+H^{3-hea}+H^{3-cul})}\right)}.
\end{aligned}
\tag{8}
$$

Relative weight indexes based on SCSCs. To avoid the possible occurrence of multiple solutions for weights, this study adopts strong complementary slackness conditions. After referring to Sueyoshi and Goto (2012) and Chen et al. (2015), this study incorporates SCSCs in the BoD model. The SCSCs-based BoD model can be expressed as follows:

$$
\begin{aligned}
&\text{Maximize } \eta\\
&s.t.\ the\ same\ sonstra\ int\ s\ in\ Models\ (5)\ and\ (6),\\
&\left[\begin{matrix}\frac{1}{H}\left[\sum_{c=1}^{C}\sum_{h\in H^c}(\beta_{hk\tau}^{y^c}+\beta_{hk\tau}^{ES^c})\right] =\\ \begin{pmatrix} -\sum_{h=1}^{H^2}u_h^2y_{hk\tau}^2-\sum_{h=H^2+1}^{H^{3-hea}}u_h^{3-hea}y_{hk\tau}^{3-hea}-\sum_{h=H^{3-hea}+1}^{H^{3-cul}}u_h^{3-cul}y_{hk\tau}^{3-cul}\\ -\sum_{h=H^{3-cul}+1}^{H^{1-ee}}u_h^{1-ee}ES_{hk\tau}^{1-ee}-\sum_{h=H^{1-ee}+1}^{H^{3-edu}}u_h^{3-edu}ES_{hk\tau}^{3-edu}+\sigma\end{pmatrix}\end{matrix}\right],\\
&\begin{pmatrix} -\sum_{h=1}^{H^2}u_h^2y_{hjt}^2-\sum_{h=H^2+1}^{H^{3-hea}}u_h^{3-hea}y_{hjt}^{3-hea}-\sum_{h=H^{3-hea}+1}^{H^{3-cul}}u_h^{3-cul}y_{hjt}^{3-cul}\\ -\sum_{h=H^{3-cul}+1}^{H^{1-ee}}u_h^{1-ee}ES_{hjt}^{1-ee}-\sum_{h=H^{1-ee}+1}^{H^{3-edu}}u_h^{3-edu}ES_{hjt}^{3-edu}+\sigma+\lambda_{jt}\end{pmatrix}\geq\eta\begin{pmatrix} j=1,\ldots,J;\\ t=1,\ldots,T\end{pmatrix},\\
&u_h^c g_{hk\tau}^{ES^c}+\beta_{hk\tau}^{ES^c} \geq 1/H+\eta\begin{pmatrix} h\in H^c;\\ c=1-ee, 3-edu\end{pmatrix},\\
&u_h^c g_{hk\tau}^{y^c}+\beta_{hk\tau}^{y^c} \geq 1/H+\eta\begin{pmatrix} h\in H^c;\\ c=2, 3-hea, 3-cul\end{pmatrix},\\
&u_h^c \geq \eta,\\
&\lambda_{jt}\geq 0, u\geq 0, \beta_{hk\tau}\geq 0, \eta\geq 0.
\end{aligned}
\tag{9}
$$

Here, η denotes nonnegative variables that can ensure the optimality of SCSCs.

In Model (9), the first additional constraint ensures that the optimal solutions of Model (5) and Model (6) are equal. The second and third additional constraints represent the complementary slackness conditions.

Based on the unique optimal weights derived from SCSCs, this study performs relative weight analysis. This type of analysis is instrumental in priority assessment, as highlighted by Zhou et al. (2022). To avoid the possible occurrence of extreme weights, this study adopts Winsorization method at the 1st percentile and 99th percentile respectively. In this context, dimension-based relative weight indexes (RW) are utilized to evaluate the relative priority of each dimension within the system. The technical definition of RW for each dimension is as follows:

$$
\begin{aligned}
RW_{jt}^{EE} &= \frac{\sum_{h\in H^{1-ee}}u_h^*/H^{1-ee}}{\sum_{h\in H^{1-ee}}u_h^*/H^{1-ee}+\sum_{h\in H^2}u_h^*/H^2+\sum_{h\in H^3}u_h^*/H^3},\\
RW_{jt}^{IC} &= \frac{\sum_{h\in H^2}u_h^*/H^2}{\sum_{h\in H^{1-ee}}u_h^*/H^{1-ee}+\sum_{h\in H^2}u_h^*/H^2+\sum_{h\in H^3}u_h^*/H^3},\\
RW_{jt}^{SD} &= \frac{\sum_{h\in H^3}u_h^*/H^3}{\sum_{h\in H^{1-ee}}u_h^*/H^{1-ee}+\sum_{h\in H^2}u_h^*/H^2+\sum_{h\in H^3}u_h^*/H^3}.
\end{aligned}
\tag{10}
$$

Here, * represents optimal solutions of Model (9).

Coupling related analysis. This study adopts the coupling degree (CD) and coupling coordination degree (CCD) to measure interaction association degree among dimensions within an integrated system (Qi et al. 2022). Here, the coupling degree is used to evaluate the association among three dimensions—economy-environment, infrastructure construction, and social development—while the coupling coordination degree is employed to gauge the development level of the sustainability system and the nature of interactions among these dimensions.

After referring to Qi et al. (2022), this study computes the coupling-related indexes in the following manner.

$$
\begin{aligned}
CD &= \frac{3\sqrt[3]{CI^{EE}*CI^{IC}*CI^{SD}}}{CI^{EE}+CI^{IC}+CI^{SD}},\\
CCD &= \sqrt{CD*F},\\
F &= \alpha^1\,CI^{EE}+\alpha^2\,CI^{IC}+\alpha^3\,CI^{SD}.
\end{aligned}
\tag{11}
$$

Here, F refers to the comprehensive index of the sustainability system. α^1, α^2 and α^3 represent the relative importance of three dimensions. For simplicity, the three dimensions are considered equally important in this study, so the values of three dimensions (α^1, α^2, α^3) are set to 1/3.

BP-DEMATEL model. This study adopts BP-DEMATEL model to identify the driving dimensions and characteristic dimensions. DEMATEL is a significant systematic analysis tool used to measure the degree of influence, the degree of influence, the degree of centrality and the degree of causality for each factor. However, the traditional DEMATEL model faces a deficiency due to its reliance on the subjective expert scoring for requisite information. To address the deficiency, the BP-DEMATEL model, introduced by Cui et al. (2013), incorporates a BP neural network to objectively assign weights, thereby replacing the need for expert scores. So this study adopts BP-DEMATEL model, after referring to Cui et al. (2013), Li et al. (2020) and Wang et al. (2022).

The BP-DEMATEL model can be implemented in the following manner.

Step 1: Solve the BP neural network model.

The dimensional efficiency scores serve as the inputs of the BP neural network model, and the overall efficiency score of the sustainability system functions as the target output. So the weight matrix W is used in the input layer and the weight vector w is used in the output layer can be obtained.

Step 2: Compute the overall weight vector.

$$\begin{gathered}\omega = |W|^{*}|\mathrm{w}|,\\ \omega = (\omega_1, \omega_2, \cdots, \omega_n).\end{gathered} \tag{12}$$

In this step, we take the absolute value of the weight matrix (W) and the weight vector (w). Then, the overall weight vector (ω) is obtained by Eq. (12).

Step 3: Calculate the direct relation matrix (M).

$$M = (m_{pq})_{n\times n} = \begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1n} \\ m_{21} & m_{22} & \cdots & m_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ m_{n1} & m_{n2} & \cdots & m_{nn} \end{bmatrix},$$
$$m_{pq} = \begin{cases} \omega_p/\omega_q,\, if\ p\neq q\,(if\ \omega_q = 0, then\ m_{pq} = 0), \\ 0,\ if\ p = q. \end{cases} \tag{13}$$

Here, m_{pq} refers to the relative importance of dimension p relative to dimension q. Each element in the direct relation matrix can be obtained by Eq. (13).

Step 4: Normalize direct relation matrix.

$$\tilde{M} = (\tilde{\mathrm{m}}_{pq})_{n\times n} = \frac{M}{\max\limits_{1\le p\le n} \sum_{q=1}^{n} m_{pq}}. \tag{14}$$

Here, $\tilde{M}$ represents the normalized direct relation matrix.

Step 5: Calculate total relation matrix (S).

$$S = (\mathrm{s}_{pq})_{n\times n} = \tilde{M}(I-\tilde{M})^{-1} \tag{15}$$

Here, I denotes the identity matrix. $(I-\tilde{M})^{-1}$ stands for the inverse of $(I-\tilde{M})$. The total relation matrix is calculated by the normalized direct relation matrix.

Step 6: Identify the driving dimensions and characteristic dimensions.

$$\begin{gathered} R = [r_p] = \sum_{q=1}^{n} s_{pq}, \\ D = [d_q] = \sum_{p=1}^{n} s_{pq}. \end{gathered} \tag{16}$$

Here, r_p represents the total influence of the pth dimension on other dimensions and it is obtained by the sum of elements in the pth row of the total relation matrix. By comparison, d_q denotes the total influence of other dimensions on the qth dimension and it is computed by the sum of elements in the qth column of the total relation matrix.

Then, the centrality of each dimension can be computed by the sum of R and D (i.e., $R+D$), where a higher value corresponds to a greater importance. The causality of each dimension can be calculated by the difference between R and D (i.e., R–D). If the value of (R–D) is negative, the dimension is identified as an effect group. Otherwise, the dimension is classified into a reason group.

Step 7: Obtain relational identification matrix.

$$\pi = \frac{\sum_{p=1}^{n}\sum_{q=1}^{n} s_{pq}}{n^2}. \tag{17}$$

Here, π denotes the average relation value. If s_{pq} is greater than π, then there exists a direct effect between the pth and qth dimensions.

The data. This study considers the efficiency of Chinese cities and each city is treated as a separate DMU. Due to the availability of data, this study examines 261 cities in mainland China. The examined periods are 2009-2018. The data are obtained from the National Bureau of Statistics of China (2010-2019), and Ministry of Housing and Urban-Rural Development (2009-2018). To account for price variations, total current assets, GDP, and education expenditure are adjusted using the GDP deflator, with 2009 as the base year. The perpetual inventory method, as referenced in Zhang et al. (2004), is employed to estimate fixed capital. To mitigate the potential for negative multipliers, data normalization is applied (observed value/(max-min)), following the approach of Sueyoshi and Goto (2018). Table 3 presents the main descriptive statistics of production variables. Furthermore, to assess the per capita level, the three desirable outputs of the infrastructure construction dimension, the two desirable outputs of the health aspect, and the one desirable output of the culture aspect (as listed in Table 3) are divided by the respective city populations.

The computation flow. The computation has four steps, as illustrated in Fig. 1.

Step 1: Calculate the overall and dimensional efficiency scores. This involves solving Models (1)–(8).

Step 2: Examine the relative priority of each dimension. For this analysis, Models (9) and (10) are employed.

Step 3: Assess the coupling coordination development level. This study uses Eq. (11) to conduct this assessment.

Step 4: Identify the driving dimensions and characteristic dimensions. To achieve this, Eqs. (12)–(17) are utilized.

Results and discussion

The multi-dimensional efficiency scores. This study begins by discussing the overall and dimensional efficiency scores of Chinese cities, with the findings presented in Figs. 2–4. These results yield four key insights.

First, the overall efficiency scores of Chinese cities exhibit a consistent upward trend over the study period (2009–2018), suggesting that China has made overall progress in promoting sustainability. In contrast, the dimensional efficiency scores present a varied picture. The infrastructure construction and social development dimensions show positive growth yet remain at relatively low efficiency levels (see Fig. 2), indicating ample room for enhancement in these areas. Conversely, the economy-environment dimension, while maintaining relatively high efficiency scores, displays a downward trend. This phenomenon can be attributed to the Chinese government's intensive efforts in environmental protection, which have led to a strategic shift in focus towards long-term sustainability dimensions such as education and infrastructure, with a corresponding reallocation of limited funds away from economic growth. Additionally, the

Table 3 Descriptive statistics of production variables of 2009–2018 of China.

Dimension	Indicator	Variable	Unit	Ave	Max	Min	SD
Economy-environment	Input	Labor	10^4 persons	50.495	754.000	4.450	71.359
		Electricity	10^4 kW	1,054,287.351	15,666,595.000	9746.000	1,650,845.326
		Fixed capital	10^4 RMB	68,712,971.157	840,125,320.000	1,511,410.458	88,905,962.853
		Current asset	10^4 RMB	8,970,530.382	147,557,727.953	80695.254	15,981,480.511
	Desirable output	GDP	10^4 RMB	8,221,952.818	174,277,408.326	169466.144	17,863,594.973
	Undesirable output	Soot (dust)	Ton	6951.365	80,468.000	60.000	8250.199
		Sulfur dioxide	Ton	49,403.737	586,117.000	212.000	51,347.169
		Waste water	10^4 tons	28,154.361	301,827.000	590.000	30,100.913
Infrastructure construction	Desirable output	Road area	10^4 m^2	1821.051	17,776.030	64.200	2323.517
		Drainage pipeline	km	1391.674	21,974.660	21.000	2379.066
		Green coverage	ha	5594.666	88,843.780	26.000	8067.190
Social development	Input	Number of education employees	10^4 persons	5.453	50.570	0.210	4.919
		Education expenditure	10^4 RMB	179,885.467	5,366,593.027	3516.838	469,895.074
	Desirable output	Student	Person	87,896.175	1,057,281.000	231.000	153,458.977
		Public library collection	10^3 books	2850.055	78,940.000	64.000	6680.776
		Hospital bed	Bed	18,661.021	177,410.000	1352.000	16,133.726
		Doctor	Person	9454.286	96,445.000	725.000	9011.011

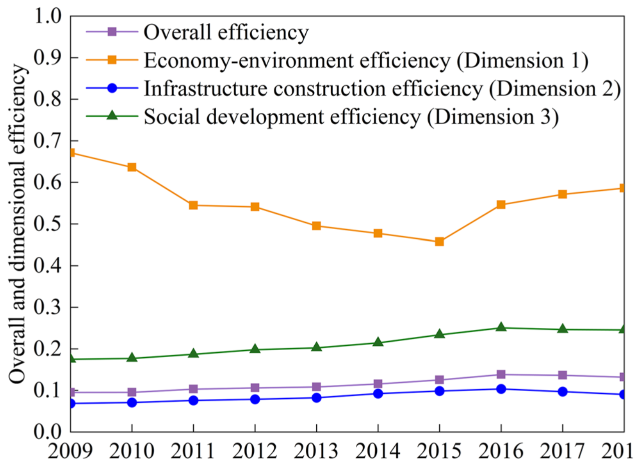

Fig. 2 Time trends of multi-dimensional efficiency scores.

environmental protection policy emphasizes economic structural transformation, energy conservation, and emission reduction, which initially results in a decline in economic efficiency during the early stages of the transformation (Zhou et al. 2020; Xu and Xu, 2023). Furthermore, the green transition policy exerts pressure on production technology to evolve, leading to increased production costs and a reduction in economy-environment efficiency (Liu et al. 2023).

Second, significant disparities exist in the overall efficiency scores among Chinese cities. Notable top performers are Shenzhen, Dongguan, Guangzhou, and Jiayuguan, with an average efficiency score of 0.844, indicating a potential for a 15.6% improvement in their efficiency. Shenzhen, Dongguan, and Guangzhou serve as benchmarks due to their high efficiency levels. Specifically, these cities perform well in the economy-environment, infrastructure construction, and social development dimensions. This is largely attributed to their strong emphasis on environmental quality protection amidst economic growth (Cui et al. 2021). Furthermore, these cities are located in the Pearl River Delta, a pivotal region for China's economic and social reforms, and their role in the reform and opening up process contributes to their success. Additionally, these cities invest heavily in infrastructure development and education, boasting high-quality transportation networks, public services, and educational systems.

In contrast, the laggard cities include Longnan, Suihua, Zhoukou, Dazhou, Zhaotong, Hechi, Bazhong, Linfen, Liupanshui, and Shangqiu. These cities possess substantial potential for enhancing their sustainability. Moreover, it is evident that most laggard cities exhibit a common characteristic: they demonstrate strong performance in the economy-environment dimension but underperform in the areas of infrastructure construction and social development. These findings indicate a disproportionate focus on economic growth at the expense of investment in education, culture, health, and infrastructure. Additionally, these cities are characterized by a relatively low level of gross output, which, coupled with financial constraints, has hindered their development in transport infrastructure, education, and health. Such imbalances may compromise long-term sustainability.

Third, the infrastructure construction dimension emerges as the most significant source of inefficiency among all dimensions. In terms of average efficiency scores, the economy–environment dimension ranks first at 0.551, followed by the social development dimension at 0.210, with the infrastructure construction dimension trailing at 0.085. These rankings are similarly reflected at the city level, as illustrated in Fig. 3. Panel 3A reveals a concentration of dots below the red line, signifying that for the majority of cities, the efficiency in the economy-environment dimension surpasses that in the infrastructure construction dimension. A similar pattern is observed in Panel 3B, where the efficiency of the economy-environment dimension is higher than that of the social development dimension for most cities. Furthermore, Panel 3C demonstrates that for most cities, the efficiency of the social development dimension is greater than that of the infrastructure development dimension. These findings indicate an imbalance in the development of the three dimensions across most cities. To mitigate this imbalance, local governments must shift their focus from economic growth to dimensions crucial for long-term

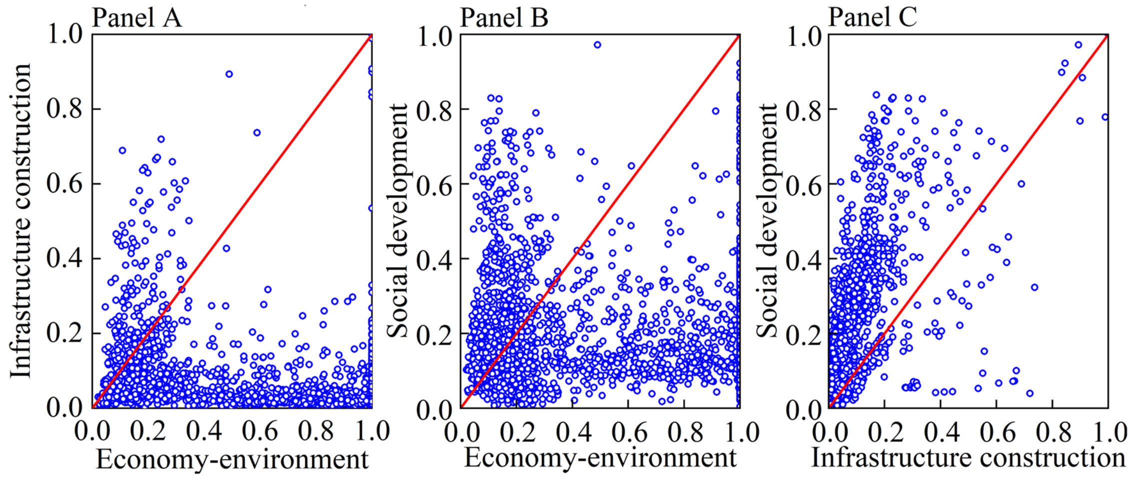

Fig. 3 Scatter plots of dimensional efficiency scores. A Efficiency of economy-environment dimension and infrastructure construction dimension. **B** Efficiency of economy-environment dimension and social development dimension. **C** Efficiency of infrastructure construction dimension and social development dimension. The horizontal and vertical axes denote the efficiency of various dimensions. The blue dots symbolize individual cities, and the red line indicates the 45° benchmark.

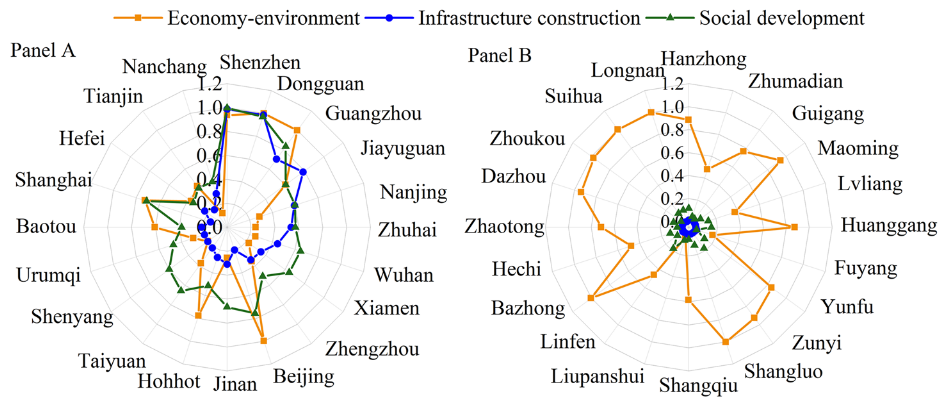

Fig. 4 The dimensional efficiency of the best performers and the laggard cities. A Dimensional efficiency of the best performers. **B** Dimensional efficiency of the laggard performers.

sustainability, such as education and infrastructure. For cities facing adverse conditions, the central government should prioritize resource allocation towards strengthening infrastructure construction to bolster their long-term sustainability.

Finally, significant disparities in development patterns are observed across Chinese cities. Based on the dimensional efficiency scores, cities can be broadly categorized into four distinct groups. The first group comprises cities such as Shenzhen, Dongguan, and Guangzhou, which perform well in all three dimensions (Fig. 4), thereby emerging as the top performers. The second group includes cities like Tongling, Zhongshan, and Foshan, characterized by high efficiency in the economy-environment dimension but low efficiency in infrastructure construction. The third group consists of cities such as Beihai, Guyuan, Lijiang, Huludao, and Baicheng, which demonstrate strong performance in the economy-environment dimension but underperform in both infrastructure construction and social development. To change the situation, these cities must intensify their efforts in the infrastructure and social development dimensions. The fourth group encompasses lagging cities like Yuncheng, Jixi, Suqian, Xingtai, Jincheng, and Liupanshui, which exhibit poor performance across all three dimensions. Aside from the first group, the remaining three groups reveal a variety of factors contributing to low sustainability efficiency. Consequently, local governments are tasked with formulating tailored strategies to enhance sustainability.

The coupling-related analysis. This subsection considers the results of coupling degree and coupling coordination degree indexes. The results are reported in Table 4 and Fig. 5. These results offer us three insightful findings.

First, Chinese cities exhibit a consistent increase in the coupling degree over the examined period (Fig. 5A). These findings indicate a relatively coordinated and balanced progress among the three-dimensional efficiency scores. This outcome is anticipated, given the numerous measures undertaken by the Chinese government to foster long-term sustainability.

However, there is substantial heterogeneity in the evolution of coupling degree indexes across Chinese cities. Notably, cities such as Bozhou, Yibin, Yichun, Heze, Xiaogan, and Xuchang have made significant advancements in their coupling degree indexes. In contrast, cities like Hengshui, Weinan, Anyang, Tieling, Laibin, and Zhangjiakou have experienced a marked decline. These results are unsurprising, as these cities have undergone uneven development among their three-dimensional efficiency scores.

Table 4 Cities with high or low coupling-related indexes.

City	Coupling degree	Comprehensive index	Coupling coordination degree
Dongguan	0.999	0.986	0.993
Shenzhen	0.995	0.973	0.983
Huizhou	0.982	0.150	0.382
Jixi	0.980	0.072	0.265
Panjin	0.968	0.172	0.406
Guangzhou	0.966	0.846	0.902
Jincheng	0.957	0.063	0.241
Wuhu	0.956	0.175	0.408
Jiayuguan	0.956	0.665	0.783
Datong	0.940	0.100	0.305
Ezhou	0.940	0.171	0.397
Wuhai	0.932	0.303	0.522
Bayannur	0.929	0.126	0.340
Urumqi	0.928	0.323	0.546
Shizuishan	0.925	0.180	0.408
Hebi	0.921	0.124	0.337
Huainan	0.919	0.118	0.329
Weihai	0.915	0.310	0.525
Zhengzhou	0.915	0.398	0.570
Liaoyang	0.911	0.177	0.398
Hefei	0.910	0.318	0.531
Xiangtan	0.910	0.221	0.446
Wuxi	0.907	0.259	0.482
Yangquan	0.907	0.152	0.371
Kunming	0.906	0.223	0.443
Liuzhou	0.904	0.147	0.364
Beijing	0.814	0.652	0.728
Liupanshui	0.780	0.040	0.172
Anshun	0.775	0.089	0.238
Meishan	0.682	0.094	0.248
Yuncheng	0.648	0.090	0.234
Fuyang	0.611	0.072	0.205
Suzhou	0.604	0.090	0.230
Xinzhou	0.597	0.109	0.238
Zhaotong	0.289	0.258	0.253
Maoming	0.277	0.343	0.307
Shangluo	0.274	0.375	0.320
Dazhou	0.241	0.344	0.286
Suihua	0.235	0.369	0.294
Bazhong	0.235	0.362	0.289
Zhoukou	0.197	0.339	0.257
Longnan	0.157	0.370	0.240

Special attention should be placed on cities with relatively low coupling degree indexes and negative growth rates, including Guigang, Shangqiu, Loudi, and Heyuan. Moreover, these cities also have comparatively low overall efficiency scores. This suggests that these inefficient cities not only face unbalanced development across various dimensions of the sustainability system but also suffer from deteriorating efficiency. Consequently, there is an urgent need for these cities to alter their current development strategies and design appropriate development modes addressing their primary challenges.

Secondly, regarding the coupling coordination degree, a general upward trend is observed. However, the results across Chinese cities are mixed. Certain cities, including Zhengzhou, Zhuhai, Kunming, Huaibei, Dongying, and Sanmenxia, exhibit pronounced upward trends. In contrast, some cities demonstrate declining trends. Notably, Xinzhou remains in a low coupling coordination stage.

Finally, substantial differences are identified in the coupled phase among Chinese cities. This study follows the classification criteria of Han et al. (2020). According to these criteria, 96 cities are classified as being in the superior coupled phase (e.g., Dongguan, Shenzhen, Huizhou, Jixi, Panjin, and Guangzhou), 94 cities are in the barely coupled phase (e.g., Dalian, Linyi, Jiaxing, Tongliao, Lianyungang, and Nanchong), and 66 cities are in the antagonistic coupled phase (e.g., Jinzhou, Suizhou, Shangrao, Lijiang, Nanyang, and Wuzhou). It is noteworthy that five cities—Dazhou, Suihua, Bazhong, Zhoukou, and Longnan—are in the separated coupled phase.

Meanwhile, similar patterns emerge regarding the coupling coordination degree. Of all the cities, nine (e.g., Suzhou, Zhaotong, Heihe, Fuyang, Liupanshui, and Longnan) are in the low coupling coordination phase, four (Dongguan, Shenzhen, Guangzhou, and Jiayuguan) are in the extreme coupling coordination phase, and 34 are in the high coupling coordination phase (e.g., Beijing, Hohhot, Nanjing, Changsha, Shanghai, and Zhuhai). The remaining cities are in a moderate coupling coordination phase.

Particular attention should be placed on the five cities experiencing low levels of both coupling degree and coupling coordination degree indices: Longnan, Zhoukou, Bazhong, Suihua, and Dazhou. These findings suggest that these cities are grappling with unbalanced growth and significant inefficiency across the three dimensions of extended sustainability. Therefore, identifying the root causes of unbalanced development and

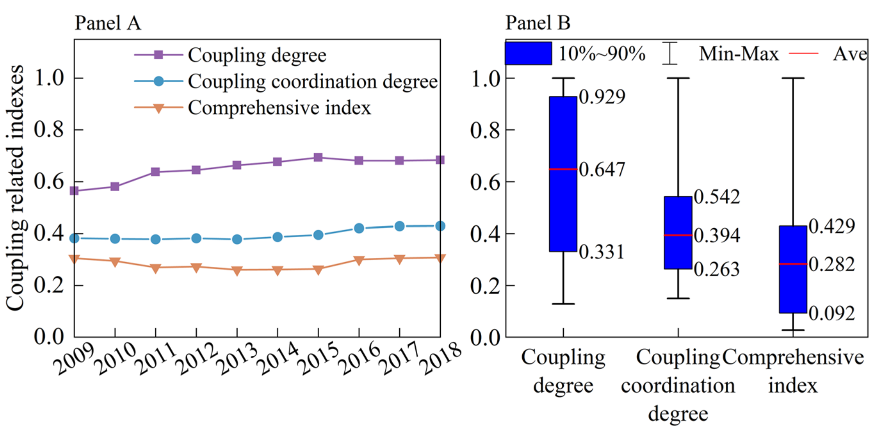

Fig. 5 Average coupling-related indexes. A Coupling-related indexes in 2009–2018. **B** Distribution of coupling-related indexes.

inefficiency is crucial for the sustainable development of these cities.

The relative priority of various dimensions. This study adopts the relative weight indexes to measure the relative priority of various dimensions within the sustainability system. The results are reported in Table 5 and Figs. 6 and 7. These results yield two significant implications.

Table 5 Cities with imbalanced relative weight indexes in three dimensions.

City	Economy-environment	Infrastructure construction	Social development
Shenzhen	0.193	0.202	0.605
Longnan	0.188	0.747	0.066
Chongqing	0.141	0.348	0.511
Suihua	0.138	0.774	0.088
Yan'an	0.138	0.752	0.110
Qingyang	0.136	0.726	0.138
Ji'an	0.136	0.706	0.158
Shangluo	0.133	0.755	0.112
Ningde	0.133	0.736	0.131
Bengbu	0.132	0.329	0.539
Datong	0.129	0.340	0.531
Lvliang	0.127	0.713	0.160
Shaoyang	0.123	0.707	0.170
Ankang	0.120	0.708	0.172
Ulanqab	0.119	0.342	0.540
Chuzhou	0.118	0.373	0.510
Hechi	0.116	0.788	0.096
Nanping	0.109	0.768	0.124
Sanming	0.108	0.745	0.147
Guang'an	0.106	0.738	0.157
Luohe	0.104	0.392	0.504
Tonghua	0.104	0.728	0.168
Yunfu	0.103	0.779	0.118
Dazhou	0.103	0.773	0.124
Yibin	0.100	0.703	0.197
Huainan	0.097	0.287	0.616
Rizhao	0.091	0.281	0.628
Linfen	0.091	0.761	0.148
Zigong	0.089	0.386	0.525
Zunyi	0.087	0.722	0.191
Shantou	0.084	0.376	0.540
Meishan	0.059	0.370	0.571
Fuyang	0.038	0.375	0.587

Firstly, the infrastructure construction dimension consistently exhibits a superior relative weight among the three dimensions throughout the examined periods. As depicted in Fig. 6, the infrastructure construction dimension boasts the highest relative weight index (0.497), signifying its paramount importance in the sustainability system. It is trailed by the social development dimension (0.343) and the economy-environment dimension (0.160). These outcomes are anticipated, given China's ongoing industrialization, which necessitates extensive infrastructure development to facilitate urbanization. In terms of social development, the Chinese populace tends to prioritize education, potentially fostering knowledge spillover effects and enhancing human capital among workers (Singh et al. 2022). Furthermore, health promotion initiatives contribute to the provision of scientific public health services and the improvement of human well-being (Mayhew et al. 2020).

Secondly, stark disparities in relative weight indexes are evident across Chinese cities, as illustrated in Fig. 7. Our results indicate that certain cities exhibit a dominant dimension. For instance, approximately 20 cities, including Hechi, Yunfu, Dazhou, Suihua, Nanping, Linfen, Shangluo, and Yan'an, place most emphasis on infrastructure construction. Additionally, 14 cities, such as Rizhao, Huainan, and Fuyang, demonstrate high relative weight in the social development dimension. The aforementioned cities may be at a relatively higher risk of unbalanced growth among the three dimensions.

The driving and characteristic dimensions. This study adopts BP-DEMATEL model to identify the driving and characteristic dimensions. The results are presented in Table 6 and Fig. 8. A significant finding emerges from these results: the economy–environment dimension serves as the driving force, whereas the infrastructure construction and social development dimensions are identified as the characteristic dimensions. This finding is implied in Fig. 8 and Table 6, which indicate a positive causality for the economy–environment dimension and a negative causality for the infrastructure construction and social development dimensions. This finding aligns with expectations, as robust economic growth facilitates advancements in infrastructure, education, and health. Consequently, the economy–environment dimension plays a crucial role in the sustainability system.

Conclusion

In this paper, we seek to investigate the complex relationship between the various dimensions of the urban sustainability system and identify key drivers to promote its sustainability more effectively. This study develops a new methodological framework to

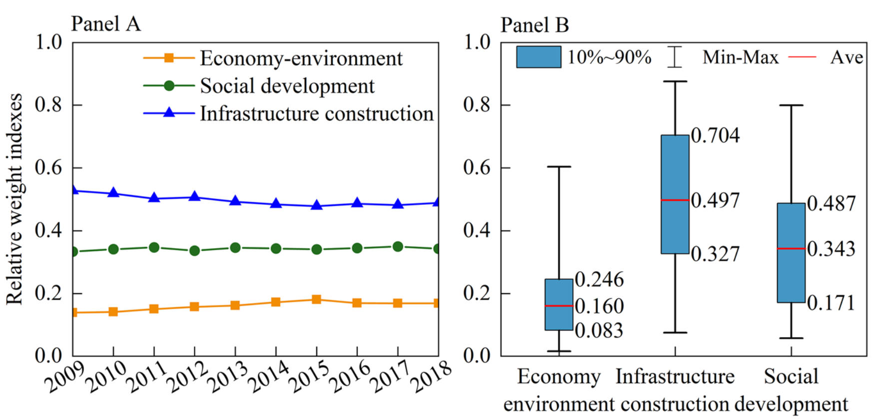

Fig. 6 Average relative weight indexes of three dimensions. A Relative weight indexes in 2009–2018. **B** Distribution of dimensional relative weight indexes.

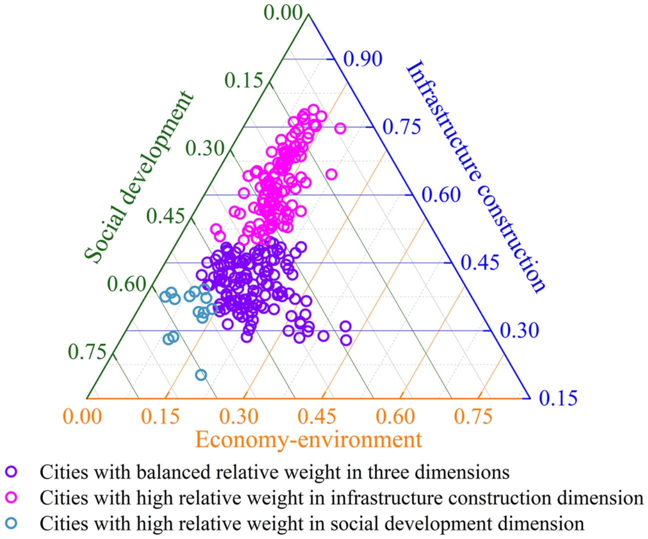

Fig. 7 Relative weight indexes of Chinese cities.

Table 6 Relational identification matrix.

	Economy-environment	Infrastructure construction	Social development
Economy-environment	0	0.682	0.981
Infrastructure construction	0	0	0.627
Social development	0	0	0

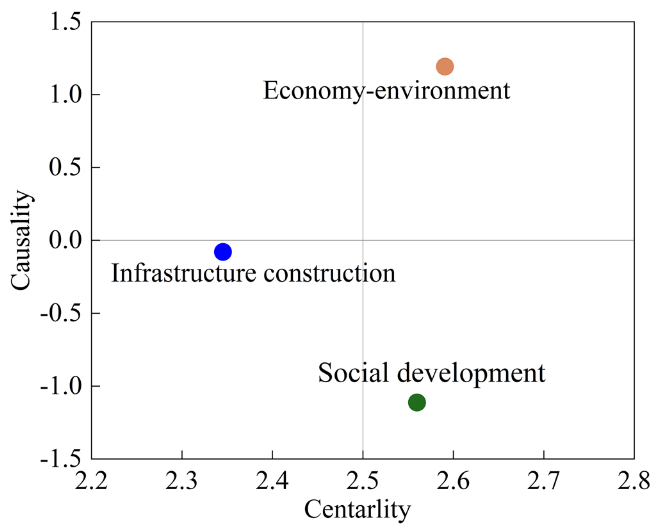

Fig. 8 The driving dimensions and the characteristic dimensions.

measure the efficiency of the urban sustainability system. In the newly expanded sustainability system, we try to evaluate multi-dimensional efficiency by incorporating internal divisions with varying structures. Specifically, we propose and apply a new DEA-based BoD model to obtain multi-dimensional efficiency measures. A notable feature of this new model is its capability to accommodate multiple divisions with varying structures. Furthermore, this study employs the BP-DEMATEL model to determine the driving and characteristic dimensions. We also use the relative weight indexes for priority analysis and coupling-related analysis to determine the degree of association between dimensions. The main conclusions and relevant policy implications are summarized as follows:

Firstly, an upward trend is observed in China's overall sustainability efficiency, suggesting commendable progress in enhancing sustainability across Chinese cities. However, there remains substantial room for efficiency improvement, as many cities exhibit low efficiency scores. To address this, particular attention should be focused on the dimensions of infrastructure construction and social development, which emerge as primary sources of inefficiency. It is crucial for governments to implement incentive mechanisms aimed at driving improvements in both infrastructure construction and social development. Furthermore, both central and local governments need to allocate additional resources to promote urban sustainable development, ensuring a more coherent and comprehensive approach to achieving higher sustainability efficiency.

Secondly, significant disparities in efficiency scores persist among Chinese cities, necessitating focused attention on cities performing poorly across all three dimensions (e.g., Longnan, Suihua and Zhoukou). In contrast, Shenzhen, Dongguan, and Guangzhou exhibit high sustainability efficiency and can serve as benchmarks for other cities. Notably, these cities prioritize environmental quality protection alongside economic growth. Moreover, these cities place significant emphasis on infrastructure construction and education, as evidenced by their well-established and high-quality transport networks, public services, and education systems, which contribute to their overall sustainable development. Consequently, the development models of these cities offer valuable insights for fostering sustainable development in other cities.

Thirdly, China demonstrates continuous improvement in both the coupling degree and coupling coordination degree, reflecting favorable progress within various dimensions of the urban sustainability system. Nonetheless, considerable disparities exist among Chinese cities, with certain cities exhibiting notably low coupling degrees and coupling coordination degrees. Cities such as Longnan, Zhoukou, Bazhong, Suihua, and Dazhou register low coupling-related indexes, indicating imbalanced growth across dimensions and significant barriers to long-term sustainability. These cities require heightened attention, with governments urged to implement tailored policies to effectively address these challenges.

Finally, the economy–environment dimension emerges as pivotal in influencing other dimensions, while the infrastructure construction and social development dimensions play crucial roles in promoting long-term urban sustainability. Our findings from the BP-DEMATEL model indicate that the economy-environment dimension remains the driving force, exerting substantial influence over other dimensions. Conversely, infrastructure construction and social development emerge as characteristic dimensions. Furthermore, relative weight analysis underscores the significance of the infrastructure construction and social development dimensions within the urban sustainability system. Given that China is a developing country, fostering economic growth is essential for sustaining infrastructure development and social progress. Simultaneously, due to the importance of infrastructure development and social development for long-term sustainability, their role within the system is indispensable. Therefore, Chinese cities need to focus on improving the efficiency of resource allocation, enhancing the ecological environment, and advancing the construction of transport infrastructure, education systems, and healthcare systems. Furthermore, it is essential for China to strengthen the role of government leadership in guiding the transition to sustainability and adhere to a sustainable development path that prioritizes ecological preservation and green development (Wang et al. 2022; Li et al. 2024).

This study acknowledges some limitations that future research can address. Specifically, within the infrastructure construction dimension, critical undesirable inputs such as waste generation, CO_2 emissions, and land degradation are absent due to the unavailability of city-level data. This data gap constitutes a limitation of our research and highlights an area for future investigation.

Data availability

The data used in this study can be found in Appendix A in the supplementary information.

Received: 28 August 2024; Accepted: 24 June 2025;
Published online: 21 July 2025

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Acknowledgements
The work was financially supported by the Project of National Social and Scientific Fund of China (No. 24CGL097), Guangdong Basic and Applied Basic Research Foundation (No. 2025A1515010620), Young Scholars of Ideology and Culture Propaganda of Publicity Department, CCCPC, Humanities and Social Sciences Research Major Project of Shandong University (Grant No. 21RWZD16), and SDU Outstanding Scholar.

Author contributions
Liqi Hu: conceptualization, methodology, formal analysis, data curation, writing original draft; Aijun Li: writing review and editing, methodology; Yunming Kuang: conceptualization, writing review and editing, visualization; Tuzhi Lin: writing review and editing.

Competing interests
The authors declare no competing interests.

Ethical approval
This paper does not contain any studies with human participants performed by any of the authors.

Informed consent
As no studies with human participants have been performed for this article, no informed consent was needed.

Additional information
Supplementary information The online version contains supplementary material available at https://doi.org/10.1057/s41599-025-05445-z.

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