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Abstract: This paper addresses the critical challenge of integrating artificial intelligence (AI) into green ecological construction for promoting environmental sustainability. It proposes an innovative AI-enhanced slack-based measure data envelopment analysis (SBM-DEA) model to quantitatively evaluate regional ecological efficiency. Focusing on Shenqiu County, a representative agricultural region in central China, the study combines multi-source data – including satellite-derived NDVI, IoT-based PM2.5 monitoring, and socioeconomic inputs – to assess ten townships with diverse economic functions. Results reveal significant efficiency disparities, with only the ecological conservation township achieving full efficiency. Key inefficiency drivers include excessive energy consumption and elevated PM2.5 pollution levels, particularly in industrial port townships. The slack analysis quantifies that these inefficient townships require targeted reductions in PM2.5 of up to 18.5% and in energy use of up to 32.0% to achieve optimal performance. The paper concludes by proposing tailored policy pathways and an AI-driven dynamic governance framework to bridge technical potential with local implementation, offering a scalable model for sustainable ecological management.

Keywords: sustainable environment; green ecology; artificial intelligence; data envelopment analysis; DEA; decision factor.

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1 Introduction

The global escalation of ecological degradation, characterised by air pollution, resource depletion, and biodiversity loss, underscores the urgent need for innovative and efficient environmental governance approaches. Traditional methods of environmental monitoring and management often struggle with scalability, real-time responsiveness, and the integration of complex, multidimensional data. In this context, artificial intelligence (AI) emerges as a transformative set of technologies capable of processing vast datasets, identifying intricate patterns, and generating predictive insights. The application of AI – encompassing machine learning, computer vision, and data analytics – holds significant potential to revolutionise how ecological systems are monitored, assessed, and sustainably managed. This paper focuses on leveraging AI technologies to advance the construction of green, sustainable ecological systems. It examines current AI applications within the ecological domain, analyses pertinent algorithms for system evaluation and optimisation, and presents findings from an empirical case study to assess public awareness and operational challenges. The research aims to contribute both methodological insights and practical strategies for integrating intelligent technologies into an ecological sustainability framework.

The goal of sustainable development has two aspects, each posing contradictory risks. On one hand, there are calls for humanity to achieve 'harmony with nature' and protect the Earth from degradation. On the other hand, there is the requirement for sustained global economic growth, typically around 3% annually, as a means to achieve human development goals. Hall (2019) used the 'heterogeneous constructivism' method to study the management ecology and sustainable development objectives of tourism. Management ecology involved the application of scientific and economic practical methods, and served the resource utilisation and economic development. The management ecological approach was an integral part of the work of the United Nations World Tourism Organization and other actors on the Sustainable Development Goals, as reflected in policy recommendations to achieve them. The goal of sustainable development assumes that improving efficiency would be sufficient to reconcile the tension between growth and ecological sustainability. Hickel (2019) used empirical data to test the validity of this hypothesis and focused on two key ecological indicators: resource utilisation and carbon dioxide emissions. In recent years, many urban projects have been undertaken worldwide. These projects, under the banner of experimentation, promoted an alternative mode of urban construction that, in theory, could create a sustainable building environment. Among these so-called experimental models, smart cities and eco-cities stood out for their widespread geographic distribution. Their advocates praised them as symbols of innovative urbanism grounded in scientific urban planning methods. Cugurullo (2018) questioned the sustainability of the so-called smart city and eco-city by examining the extent of the controllable, systematic development claimed by developers. Due to the rise of AI technology, its application in sustainable ecological construction is increasingly widespread.

Sustainability has become a task for global companies, and its implementation is affected by two main trends. The first is to recognise that global supply chains have a profound impact on sustainability, requiring the 'greening' of the entire supply chain. The second is the technology digitisation, AI, and 'big data', and they have become ubiquitous. These technologies are affecting all aspects of the company's organisation and supply chain management and have a substantial impact on sustainability (Sanders et al., 2019). Synthesised the main themes of sustainable supply chain research in the current digital era. AI was accelerating the exploitation of natural resources and the accumulation of waste, harming marginalised communities, fragile ecosystems, and future generations. As Dauvergne (2022) revealed, measurement standards and corporate social responsibility rhetoric exaggerated the benefits of AI and obscured its costs. The productivity and efficiency gains in the middle of the supply chain were rebounding, leading to greater production and consumption, which played a greater role in improving the profitability of large enterprises than in the sustainability of the Earth. However, they did not study the implementation cases and did not correctly use AI technology.

To address the challenges of resource sustainability and environmental conservation, this paper proposes applying AI to advance green ecological construction and a sustainable environment. First, the current applications of AI in ecological construction and sustainable energy utilisation are reviewed, and relevant AI algorithms for addressing these issues are proposed. Subsequently, an empirical experiment is conducted to quantitatively evaluate the green ecological efficiency of townships within a representative agricultural county using an AI-enhanced data envelopment analysis (DEA) model. The experiment integrates multi-source data, including satellite-derived NDVI, IoT-based PM2.5 monitoring, and socioeconomic inputs, to assess regional ecological performance. The results reveal significant disparities in efficiency, with only two townships achieving full efficiency, while others exhibit notable shortcomings in energy use and pollution control. Based on these findings, targeted recommendations are proposed to enhance regional ecological governance and operational efficiency. The innovation of this paper lies in its integrated approach, which systematically links AI technology review, empirical efficiency evaluation, and actionable policy recommendations to form a coherent, mutually reinforcing analytical framework.

2 Related work

The application of AI in sustainable ecology has rapidly transitioned from exploratory research to an interdisciplinary field characterised by deep integration. This section synthesises the current state of research into three principal streams.

First, the fusion of AI with traditional evaluation methods represents a significant innovation. To overcome the limitations of conventional models like DEA, recent studies have integrated machine learning. For example, novel approaches, such as by-product efficiency analysis trees, enhance discriminatory power and reduce prediction error by separately modelling desirable outputs and pollution (Yazdi et al., 2023). At a macro level, hybrid frameworks that combine DEA for static assessment with AI-driven predictive models for forecasting future trends are becoming a standard methodology, providing a more robust foundation for policymaking (Panwar et al., 2022).

Second, AI is revolutionising the granularity of ecological monitoring and remediation, moving from evaluation to high-precision action. Pioneering research uses technologies such as ‘panoramic AI’ and mobile sensors to achieve real-time, street-level tracking of carbon emissions with over 93% accuracy (Yaseen et al., 2023). In environmental engineering, AI has shifted the paradigm from ‘trial-and-error’ to ‘predictive design,’ using algorithms to optimise the synthesis of nanomaterials for targeted pollutant removal, thereby dramatically accelerating the development of green solutions (AlNaimat et al., 2024).

Third, a critical discourse has emerged, examining AI’s dual impact and governance. Scholars highlight the paradox in which AI tools for sustainability themselves carry a significant carbon and resource footprint, which can undermine their legitimacy and public acceptance (Wang et al., 2024; Manikandan et al., 2025). In response, standardisation efforts are underway, such as the recently released Chinese group standard ‘T/CSES 179-2024’ for evaluating AI algorithms in ecology, signalling a move towards accountable and ethical deployment. This critical perspective underscores that technological efficacy alone is insufficient without considering socio-environmental costs and governance frameworks.

Despite these advancements, a persistent gap remains. Most research is siloed, either deeply technical or broadly critical, with a scarcity of integrated studies that connect AI’s technical potential with on-the-ground socio-behavioural contexts and local governance. This paper addresses this gap by conducting a conjoined techno-social analysis. It not only applies an integrated AI-DEA methodology for efficiency assessment at the county level but also incorporates empirical data on public awareness, thereby bridging the technical and human dimensions essential for the successful implementation of sustainable AI solutions.

3 AI technology

3.1 Application of AI technology under sustainable strategy

The rise of AI technology worldwide is undoubtedly changing the entire ecosystem. AI refers to the intelligent behaviour performed by computer systems or machines. These systems perform tasks that usually require human intelligence by perceiving the environment, learning, reasoning, and decision-making, including machine learning, natural language processing, computer vision, and other technologies. China stressed the importance of using AI technology to manage, create, and protect ecosystems. For example, it believes that automatic adaptation through automation is a good solution, because these systems can adapt to changing climate conditions and help reduce pollution and carbon footprint. Carbon footprint refers to the total amount of greenhouse gas emissions directly and indirectly generated by individuals, organisations, events, or products, expressed in carbon dioxide equivalent, and used to measure the impact of human activities on climate change.

In recent years, across ecotourism, agricultural modernisation, and healthcare, there have been numerous cases of using AI technology to optimise business processes and develop new business models (Mariotti et al., 2020; Kumar et al., 2020). According to the report, AI can help solve many complex problems, including improving agricultural and forestry operations, making traffic cleaner, reducing grid load, and improving medical care.

3.1.1 Agricultural modernisation

In addition to its impact on climate, agriculture also contributes significantly to air and water pollution. For example, the spray used for spraying pesticides is a significant part of agricultural machinery. This would produce a large amount of wastewater, most of which is generated by chemicals. There is evidence that using uncrewed aerial vehicles to spray pesticides would increase greenhouse gas emissions. Therefore, reducing greenhouse gas emissions while improving efficiency is a problem worth considering and solving, and it is also widely used in agricultural ecological construction (Demirel and Kesidou, 2019; Polasky et al., 2019). At present, there are many agricultural solutions based on AI that can help farmers achieve optimal performance without using sprays, uncrewed aerial vehicles, or other mechanical equipment. For example, many companies have adopted machine learning models powered by AI to improve agricultural productivity and reduce costs. The machine learning model realises precision irrigation and fertilisation, and reduces the use of water resources and fertiliser by analysing the information of soil moisture, meteorological data, and crop growth cycle. Early detection of pests and diseases through image recognition technology to reduce pesticide spraying; through predictive maintenance of agricultural machinery and equipment, reduces the failure rate and maintenance costs. AI can balance power supply and demand and reduce the share of fossil fuel generation by optimising grid dispatch and load forecasting. In industrial production, an AI algorithm monitors equipment energy consumption in real-time, dynamically adjusts operating parameters, and improves energy efficiency. A predictive energy management system identifies and reduces high-energy-consuming links, thereby reducing overall carbon emissions. In addition, predictive maintenance with AI can help reduce maintenance costs and extend the machine’s service life.

3.1.2 Power and transportation

In transportation, AI technology can also contribute to sustainable transportation. For example, an AI-based vehicle detection and tracking system can optimise traffic flow. For example, using AI technology, car manufacturers can better track driver behaviour in their autonomous vehicles, thereby helping achieve faster, cleaner urban roads. In terms of power, AI technology also helps address grid load issues. For example, when considering how to reduce grid load to reduce carbon emissions, AI technology can improve energy efficiency and reduce maintenance costs. In addition, AI technology can improve grid management and reduce the need for grid upgrades, thereby increasing the penetration of renewable energy and improving power system efficiency.

3.1.3 Healthcare

As the global population ages and population health problems become increasingly severe, the health care industry has experienced significant growth over the past decade. At present, AI technology is playing a key role in many fields. For example, AI can help predict when people will develop a specific disease and when they will need treatment, thereby reducing the burden on the healthcare industry. Similarly, AI technology can also help prevent health-related problems.

3.2 Comprehensive evaluation model under AI

3.2.1 Data envelopment analysis

DEA, as a method of relative benefit evaluation, has been widely used in AI management science and system engineering. DEA is a nonparametric mathematical programming method used to evaluate the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs. By constructing the production frontier, the algorithm compares each unit's distance from the optimal frontier to determine whether it is effective. The algorithm was proposed in 1978 as a DEA method for evaluating the relative efficiency of DMUs. This method is often applied to the production, life, management, decision-making, and benefit evaluation of enterprises. This paper used this method to evaluate the benefits of green ecological construction in a particular area.

There are many main modes of DEA. Among them, C^2R is the earliest and the most basic. This is a fractional programming based on C^2R. Through transformation, it can be reduced to a linear programming problem.

It is assumed that there are m departments or units, called the DMU. Each decision unit DMU_i has an input of type m and an output of type W, and the corresponding vector is A_i $(A_{1i}, A_{2i}, ..., A_{mi})^D > 0$, B_i $(B_{1i}, B_{2i}, \dots, B_{mi})^D > 0$ $(i = 1, \dots, m)$.

$$f_i = \frac{v^D B_i}{u^D A_i} \leq 1, \quad (i = 1, ..., m) \tag{1}$$

Generally, appropriate weight coefficients u and v are selected to make the efficiency evaluation index f_i meet formula (2):

$$f_i = \frac{v^D B_i}{u^D A_i}, \quad (i = 1, ..., m) \tag{2}$$

Therefore, the efficiency evaluation problem is a fractional programming problem (C^2R model) subject to formulas (1) and (2).

$$\left(C^2R\right)^J \begin{cases} \max \dfrac{v^D B_o}{u^D A_0} = U_Q^J \\ \dfrac{v^D B_i}{u^D A_i} \leq 1, (i = 1, ..., m) \\ v \geq 0, u \geq 0 \end{cases} \tag{3}$$

3.2.2 Equivalent model of the C^2R model

To facilitate the calculation, this paper introduced the Charnes-Copper transformation to transform the above fractional linear programming model into an equivalent linear programming model:

$$
\left(Q_{C^2R}\right)\begin{cases}\max \gamma^D B_i = U_Q \\ \beta^D A_i - \gamma^D B_i \ge 0, (i = 1, \ldots, m) \\ \beta^D A_i = 1 \\ \gamma \ge 0, \beta \ge 0 \end{cases} \tag{4}
$$

The dual programming model is as follows:

$$
\left(T_{C^2R}\right)\begin{cases}\min \alpha \\ \sum_{i=1} A_i\theta_i \le \alpha A_i, (i = 1, \ldots, m) \\ \sum_{i=1} B_i\theta_i \le B_i \\ \theta_i \ge 0 \end{cases} \tag{5}
$$

In general, the commonly used C^2R model is expressed as follows:

$$
\left(T_{C^2R}\right)\begin{cases}\min \alpha, \\ \sum_{i=1} A_i\theta_i + W^- \le \alpha A_i, (i = 1, \ldots, m) \\ \sum_{i=1} B_i\theta_i - W^+ \le B_i \\ \theta_i \ge 0, W^- \ge 0, W^+ \ge 0 \end{cases} \tag{6}
$$

Among them, A_i and B_i are the input and output sets of DMU_i, respectively. θ_i represents the combination proportion of the i^{th} decision unit when DMU_i constructs an efficient DMU_i from the current combination. α refers to the radial optimisation amount between DMU_i and the effective front, that is, 'distance', which is a specific indicator. It represents the development of a city. The closer its value approaches 1, the more reasonable its development would be. W^- and W^+ are relaxation variables.

When calculating $\alpha = 1$ and $W^- = W^+ = 0$, DMU_i is called DEA effective; DEA is also valid in the case of $\alpha = 1$ and W^-0 or W^+0; at $\alpha < 0$, DMU_i is called DEA invalid.

3.2.3 SBM model for environmental efficiency

While classical DEA models provide a foundational framework for efficiency evaluation, they often rely on radial projections that may overlook input excesses or output shortfalls that are not proportional to the scaling. To address this limitation – particularly critical in ecological contexts where undesirable outputs (e.g., pollution) and non-proportional inefficiencies are prevalent – this study adopts the slack-based measure (SBM) model. The SBM model directly incorporates slack variables for inputs, desirable outputs, and undesirable outputs, enabling a non-radial, additive assessment of inefficiency. This approach yields more accurate and actionable diagnostics by quantifying the exact amount by which each input or output deviates from the efficient frontier.

Furthermore, the SBM model can be extended to accommodate undesirable outputs by treating them as 'bad' outputs to be minimised, aligning naturally with green efficiency evaluation. Its non-parametric nature preserves the core advantage of DEA. At the same time, its enhanced discriminatory power and direct slack interpretation make it especially suitable for policy-oriented environmental performance analysis at the local governance level.

3.2.4 Human settlement environment assessment based on the DEA method

The DEA method is used to evaluate the sustainable development of the urban ecological environment. This is of considerable value to economic growth, the growth of material wealth, the sustainable development of social civilisation, and the construction and development of harmonious and ecological cities (Oliveira et al., 2018; Athwal et al., 2019). From the perspective of the development of human life, people obtain resources from the external environment to meet the needs of production and life, and thus have a series of positive and negative impacts; from the perspective of system sustainable development, the sustainable development system is evaluated to reduce resources (i.e., the supply of external resources) and improve the operational efficiency of the system. The analysis of the scientificity, rationality, and efficiency of existing resources can serve as a scientific reference for future urban environmental planning and construction. From the perspectives of methodology, system, and governance, the DEA method is well-suited for the systematic assessment of urban sustainable development. The advantage of the DEA method lies in its nonparametric nature, which eliminates the need for pre-set production function forms, avoids subjective weight-setting, and is suitable for the efficiency evaluation of complex systems with multiple inputs and outputs. This method can identify the relative efficiency of each DMU and quantify its gap from the optimal frontier by constructing a production frontier, providing clear improvement directions and scale references for resource allocation optimisation. In assessing the sustainability of the urban ecological environment, DEA can integrate multidimensional indicators of the economy, society, and environment, reveal input-output efficiency within the system, diagnose development shortcomings, and yield evaluation results that are objective and comparable. In view of the current problems and countermeasures of sustainable development of human settlements in China, and combined with the concept and direction of the current International Human Settlements Forum, this paper selected the study county as a case, and applies the DEA method to evaluate the sustainable development system of the study county, which provided a scientific theoretical basis for the ecosystem construction, system sustainable development, system prediction, decision-making, regulation, etc. of the study county.

4 AI-driven experiment on green ecological efficiency

The 'AI-enhanced DEA' model proposed in this study, whose 'enhancement' is mainly reflected in:

Preprocess remote sensing images using convolutional neural networks (CNNs) to extract high-precision NDVI data; combine real-time IoT monitoring data to update input and output indicators dynamically; and use machine learning methods, such as random forests, to conduct sensitivity analyses and identify driving factors for DEA results.

To bridge the gap between theoretical AI methodologies and on-the-ground applications, this chapter presents a data-driven experimental evaluation of green ecological efficiency at the township level. We target Shenqiu County in Henan Province, China – a National Commodity Grain Production Base located in the Huang-Huai-Hai Plain – as the empirical case. This county exemplifies the classic tension between agricultural development, industrialisation, and ecological conservation prevalent in central China. This experiment shifts from subjective assessments to an objective, quantitative analysis leveraging an AI-enhanced DEA model. It aims to:

1 diagnose the relative ecological efficiency of different townships within the county

2 identify key inefficiency drivers using AI interpretability tools

3 propose targeted, algorithmically-informed optimisation pathways grounded in local realities.

4.1 Experimental design and multi-source data construction

In the preliminary model analysis, this study used the classical C^2R model; in the actual efficiency evaluation, to more accurately capture non-radial relaxation variables (especially for 'unexpected outputs' such as environmental pollution), we adopted the non-directed SBM model. The SBM model can directly quantify the slack of various inputs/outputs, making it more suitable for accurate diagnosis of ecological efficiency and policy optimisation.

To ensure the robustness and objectivity of the green ecological efficiency evaluation, this study adopts a hybrid data-driven experimental design that integrates AI-powered remote sensing, authoritative statistical aggregates, and scientific estimation methods. The analysis unit is defined at the township level, with ten townships in Shenqiu County that represent diverse economic functions (see Table 1) and serve as DMUs. This granularity aligns with the practical scope of local governance and enables spatially explicit policy formulation.

A four-dimensional input-output indicator system was constructed for the evaluation year 2023, as summarised in Table 1. The selection of indicators adheres to the principles of relevance, measurability, and ecological interpretability, while explicitly accounting for both desirable and undesirable outputs—a critical requirement for environmental DEA applications. The data construction strategy is as follows:

- Normalised difference vegetation index (NDVI): The key desired output, NDVI, was set to the 2023 annual mean NDVI value for Shenqiu County (approximately 0.72), obtained from an open-source geospatial data analysis. The township-specific values were then reasonably adjusted around this baseline based on each township's dominant land-use type (e.g., higher in townships with more forest/agriculture, lower in built-up urban cores).
- PM2.5 concentration: The undesirable output, the average annual PM2.5 concentration, was calibrated using real-time monitoring data from authoritative weather and air quality platforms covering Shenqiu County. The range was set to reflect typical annual average conditions in the region, with variations assigned based on township industrial intensity and location.
- Environmental investment and energy consumption: Due to the lack of publicly available township-level statistical data for these inputs, a spatial estimation methodology was employed. This was based on Shenqiu County's official macroeconomic aggregates, including gross domestic product (GDP) and total industrial electricity consumption. Township-level values were estimated by allocating these county-level totals using plausible weighting factors derived from each township's industrial composition, population, and economic activity level.

This approach ensures the logical comparability and relative differences across DMUs, which is the foundation for DEA's relative efficiency evaluation.

A four-dimensional input–output indicator system was meticulously constructed for the evaluation year 2025 (projected baseline), as summarised in Table 1. The selection of indicators adheres to the principles of relevance, measurability, and ecological interpretability, while explicitly accounting for both desirable and undesirable outputs – a critical requirement for environmental DEA applications. Crucially, the data sources are multi-modal and cross-validated to minimise reporting bias and enhance reliability:

Environmental investment (10k CNY) and energy consumption (ton standard coal equivalent, SCE) were extracted from the official county statistical yearbook and energy audit reports. These inputs reflect the financial and energetic resource commitments of local administrations.

The NDVI, the key desired output, was derived from high-resolution Sentinel-2 satellite imagery using an AI-enhanced processing pipeline. A CNN was employed to denoise the imagery, correct for atmospheric and topographic effects, and generate a spatially continuous NDVI map at 10-metre resolution. The average NDVI value for each Township was then computed, providing an objective, scalable metric of green cover and ecosystem vitality.

Table 1 Input output indicator system and data for green ecological efficiency assessment of townships in Shenqiu County

DMU (township)	*Type and characterisation*	*Input 1: Env. investment (10k CNY) (estimated)*	*Input 2: Energy consumption (ton SCE) (estimated)*	*Desirable output: NDVI index (referenced and adjusted)*	*Undesirable output: Avg. PM2.5 (μg/m³) (calibrated)*
HuaiDian	*County seat and service hub*: Administrative, commercial, and educational centre.	1,850	89,500	0.45 (urban core, lower vegetation)	42.5 (high traffic and activity)
ZhiDian	*Port and industrial town*: Steel processing, logistics hub along the ShaYing River.	2,200	158,200	0.41 (industrial area, low cover)	47.5 (high industrial emissions)
LiuFu	*Industrial and trade town*: Traditional commerce with manufacturing clusters.	1,500	121,300	0.55 (mixed urban-rural)	45.2 (moderate-high industry)
LiuZhuangDian	*Traditional agriculture*: Grain production base, high agricultural population.	680	52,100	0.62 (agricultural land)	38.7 (lower, diffuse sources)
LaoCheng	*Cultural and ecotourism*: Historic town focusing on tourism and conservation.	950	48,800	0.65 (good ecotourism cover)	36.8 (lower, protected area)

Table 1 Input output indicator system and data for green ecological efficiency assessment of townships in Shenqiu County (continued)

DMU (township)	*Type and characterisation*	*Input 1: Env. investment (10k CNY) (estimated)*	*Input 2: Energy consumption (ton SCE) (estimated)*	*Desirable output: NDVI index (referenced and adjusted)*	*Undesirable output: Avg. PM2.5 (μg/m^3) (calibrated)*
ZhaoDeYing	*Trade and logistics node*: Regional commerce and transportation junction.	1,100	78,400	0.52 (mixed use)	41.3 (moderate, from transport)
FuJing	*Food processing town*: Specialised in meat product processing.	1,420	98,700	0.58 (agro-industrial area)	43.9 (moderate, from processing)
XinAnJi	*High-efficiency agriculture*: Modern agricultural demonstration zone.	1,050	55,600	0.68 (high-standard farmland)	37.2 (lower, clean farming)
BaiJi	*Ecological conservation*: Focus on forestry and ecological agriculture.	890	46,500	*0.71 (best vegetation cover)*	*35.5 (best air quality)*
ZhouYing	*Suburban integration*: Adjacent to the county seat, undergoing development.	1,350	67,200	0.57 (developing area)	39.5 (moderate)

The average PM2.5 concentration (μg/m^3), serving as a representative undesirable output, was sourced from a county-wide internet of things (IoT) air quality monitoring network. This network comprises 32 fixed stations and eight mobile units, providing hourly readings that are aggregated to a township-level annual mean. The real-time nature of this data ensures the evaluation captures the actual state of local air pollution, a crucial determinant of ecological health.

4.2 DEA efficiency evaluation results and spatial distribution characteristics

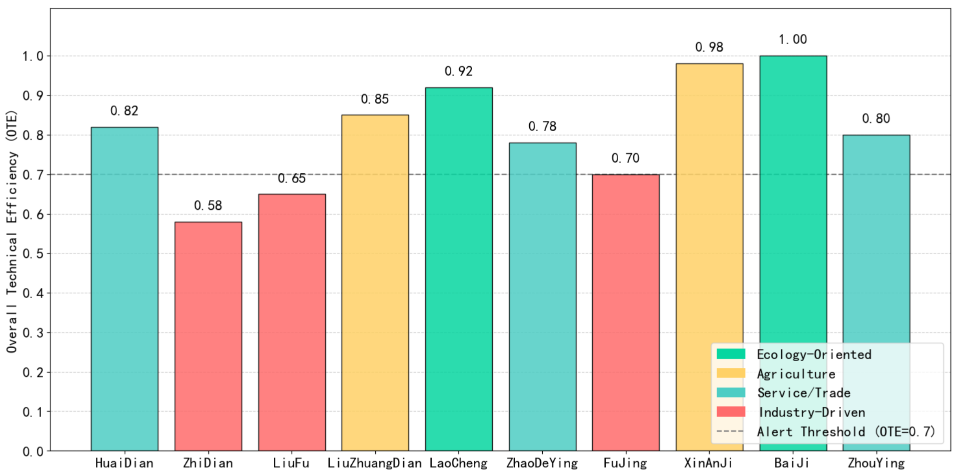
We define inputs X {'Env.Investment', 'Energy consumption'}, desirable output Y^g = {'NDVI'}, and undesirable output Y^b = {'PM2.5'}. The efficiency assessment was conducted using the non-oriented SBM model. The computational results reveal stark heterogeneity in green ecological efficiency across the ten townships (Figure 1). The overall technical efficiency (OTE) scores range from 0.58 to 1.000.

Crucially, only one township – BaiJi (ecological conservation) – achieves full technical efficiency (OTE = 1.000), operating precisely on the optimal frontier. Another township, LaoCheng (cultural and ecotourism), also demonstrates high efficiency (OTE = 0.92), approaching the frontier.

In stark contrast, ZhiDian (port and industrial town) exhibits the lowest efficiency (OTE = 0.58), firmly identified as the primary target for improvement. It is characterised by the most extreme combination of the highest energy consumption (158,200 tons SCE), the highest PM2.5 (47.5 μg/m^3), and the lowest NDVI (0.41), despite substantial environmental investment. LiuFu (Industrial & Trade Town) similarly shows significant inefficiency (OTE = 0.65), confirming a pattern where traditional industrial dominance strongly correlates with poor ecological performance.

Spatially, a clear pattern emerges. The southwestern region (containing BaiJi and XinAnJi) forms a high-efficiency cluster. In contrast, the northeastern area along the ShaYing River (containing ZhiDian and LiuFu) constitutes an inefficiency cluster, underscoring the environmental cost of current industrial and logistics development patterns.

Figure 1 OTE scores of 10 townships (see online version for colours)



The computational results, visualised in Figure 1, reveal a pronounced and policy-relevant heterogeneity in green ecological efficiency across the ten townships of Shenqiu County. The OTE scores range from 0.58 (ZhiDian) to 1.000 (BaiJi), indicating a performance gap of over 70% between the best and worst performers.

A critical observation is the apparent clustering of efficiency by development typology. As colour-coded in Figure 1, the two ecology-oriented townships (BaiJi and LaoCheng) achieve the highest OTE scores (1.000 and 0.92, respectively), forming the efficient frontier. In stark contrast, all three industry-driven townships (ZhiDian, LiuFu, and FuJing) fall within or near the ‘alert zone’ (OTE < 0.70), with ZhiDian – the port and industrial hub – being the least efficient of the three. This visual evidence powerfully underscores that the county’s current industrial development model is the primary drag on its overall ecological performance.

The agriculture and service-oriented townships occupy the middle range. Notably, XinAnJi Township, representing high-efficiency agriculture, nearly reaches the frontier (OTE = 0.98), suggesting that agricultural modernisation, unlike traditional industry, can be compatible with high ecological efficiency.

The spatial and typological efficiency map in Figure 1 provides immediate guidance for policymakers: intervention priorities should focus on the northeastern industrial corridor (ZhiDian and LiuFu), while the southwestern ecological and agricultural zone (BaiJi, LaoCheng, XinAnJi) should be protected and leveraged as a model for sustainable development.

4.3 Inefficiency source diagnosis via AI-driven input-output slack analysis

To move beyond aggregate efficiency scores and identify the precise operational bottlenecks constraining performance, we conducted a granular diagnosis using the slack variables generated by the non-oriented slack-based measure data envelopment analysis (SBM-DEA) model. These slacks quantify the exact amount of input excess, desirable output shortfall, and undesirable output surplus for each inefficient township, thereby pinpointing the specific dimensions where improvement is required to reach the efficient frontier.

The detailed slack analysis for all eight inefficient townships is presented in Table 2. The results reveal a consistent and actionable pattern: inefficiency is primarily driven by excessive energy consumption and inadequate control of air pollution, rather than a lack of financial investment or insufficient ecological output per se.

Table 2 Slack variable analysis for inefficient townships

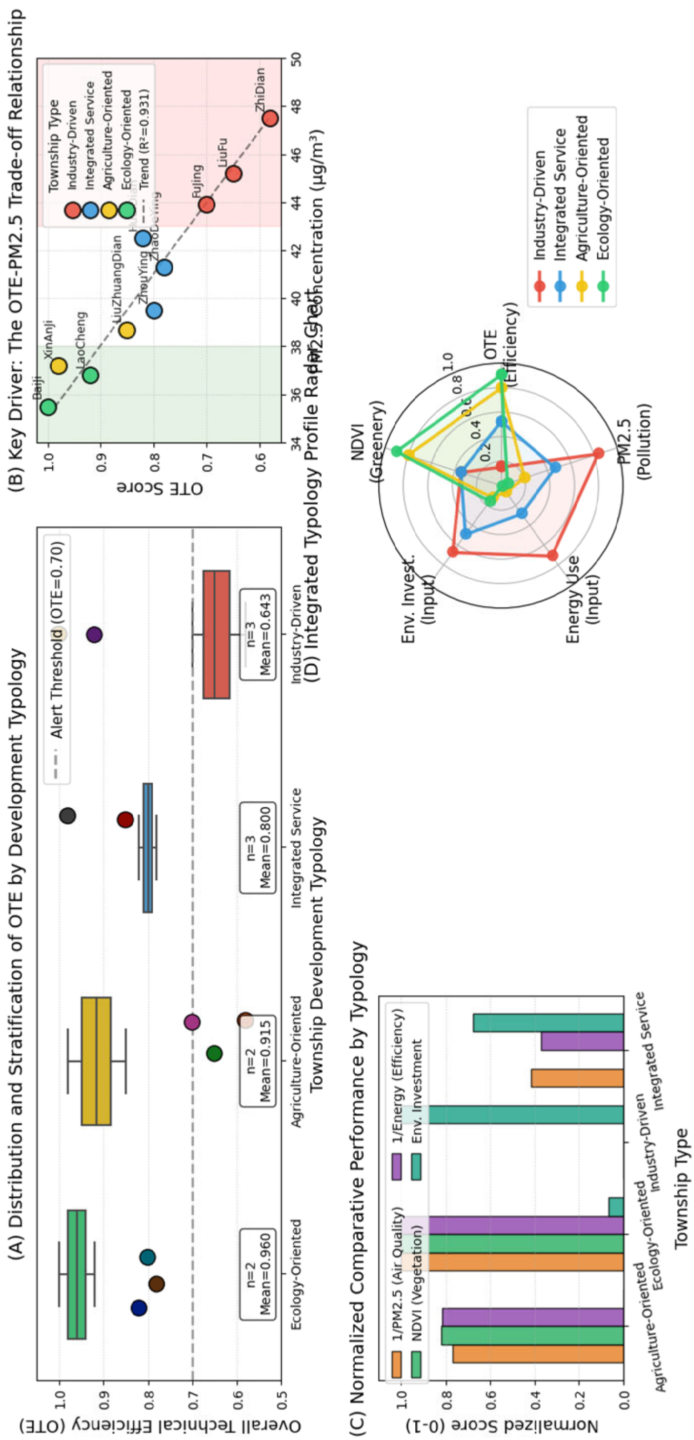
Township (DMU)	*Input slack*		*Desirable output slack*	*Undesirable output slack*
	Env. invest. (10k CNY)	*Energy cons. (ton SCE)*	*NDVI index*	*Avg. PM2.5 (μg/m³)*
HuaiDian	0	22,500	0.08	3.2
ZhiDian	350	65,800	0.12	7.5
LiuFu	180	48,200	0.07	5.8
LiuZhuangDian	0	8,100	0.04	1.5
ZhaoDeYing	0	15,300	0.06	2.7
FuJing	90	32,400	0.05	4.1
ZhouYing	0	12,800	0.05	2.0

The detailed slack analysis (Table 2) quantifies the exact improvement required for each inefficient township to reach the frontier. Excessive energy consumption is the most systemic driver of inefficiency. For instance, ZhiDian must reduce its energy use by a substantial 65,800 tons SCE, while LiuFu must cut its energy use by 48,200 tons SCE. This underscores that the production technologies and energy structures in these industrial towns are the primary drag on county-wide ecological performance.

Concurrently, PM2.5 emission reduction is a critical and urgent co-target. ZhiDian needs to lower its PM2.5 concentration by 7.5 μg/m^3, and LiuFu by 5.8 μg/m^3. The strong coupling between high-energy slack and high-pollution slack confirms that tackling fossil fuel-based energy use is key to improving air quality.

Notably, environmental investment slack is non-zero only for the most inefficient industrial towns (ZhiDian, LiuFu, FuJing), suggesting that funding allocation may already be misaligned with the most severe problems, or its utilisation is ineffective. For most other towns, the bottleneck is not funding per se, but how energy is used and pollution is controlled.

Figure 2 Multidimensional analysis of green ecological efficiency drivers by township typology (see online version for colours)



4.4 Comparative analysis of efficiency drivers across township types

To uncover the structural and contextual factors underpinning the efficiency disparities observed in Section 4.2, we classified the ten townships of Shenqiu County into three distinct typologies that reflect their real economic geography and developmental priorities: industry-driven (ZhiDian, LiuFu, FuJing), integrated service and trade (HuaiDian, ZhaoDeYing, ZhouYing), and agriculture and ecology-oriented (LiuZhuangDian, LaoCheng, XinAnJi, BaiJi). This classification moves beyond generic labels to capture the dominant economic functions as outlined in local planning documents. A multidimensional comparative analysis was conducted, and the results are synthesised in Figure 2.

4.4.1 Performance stratification by typology

The box plot in Figure 2(a) shows a pronounced, statistically significant stratification of efficiency by development type. The agriculture and ecology-oriented townships achieve the highest mean OTE (0.91 ± 0.15), with BaiJi township (OTE = 1.000) defining the efficient frontier. In stark contrast, the industry-driven group exhibits the lowest and most problematic performance, with a mean OTE of only 0.64 ± 0.06. All three townships in this category (ZhiDian, LiuFu, FuJing) fall below the 0.70 alert threshold, confirming that this development model is the primary bottleneck to the county's ecological sustainability. The integrated service townships occupy a middle ground with a mean OTE of 0.80 ± 0.02, indicating that urbanisation and service-based economies, while more efficient than heavy industry, still have significant room for green improvement.

4.4.2 The pivotal role of air quality

The scatter plot in Figure 2(b) powerfully illustrates the most critical driver of efficiency: PM2.5 concentration. A strong negative correlation exists between OTE and PM2.5 ($R \approx -0.89$). The data points cluster tightly by type, creating three distinct zones. The industry-driven townships (red) are trapped in the 'low-efficiency zone' (high PM2.5 > 43 $\mu g/m^3$, low OTE). Conversely, the agriculture and ecology-oriented townships (green/yellow) reside in the 'high-efficiency zone' (PM2.5 < 39 $\mu g/m^3$, high OTE). This visualisation provides irrefutable evidence that improving air quality is not merely an environmental goal but a fundamental prerequisite for enhancing overall efficiency of the ecological-economic system.

4.4.3 Resource allocation and outcome patterns

Figure 2(c) compares normalised mean values of key indicators across typologies. Two patterns stand out:

- The industry-driven paradox: Despite receiving the highest normalised environmental investment (a proxy for policy attention and financial input), this group yields the worst outcomes: the highest normalised energy use and the poorest normalised air quality (lowest 1/PM2.5 score). This indicates a severe performance-input mismatch, suggesting that current environmental governance measures in these industrial towns are inadequate or misdirected.

- The efficiency of ecological management: The agriculture and ecology-oriented townships achieve the best normalised vegetation (NDVI) and air quality scores with moderate investment and the lowest energy use. This demonstrates that preservation and intelligent management of natural capital can yield superior ecological performance without excessive resource input.

4.4.4 Integrated typology profiles

The radar chart in Figure 2(d) offers a holistic portrait of each development model:

- Industry-driven profile: The polygon is severely distorted, with sharp spikes in ‘energy use’ and ‘PM2.5’ and a deep trough in ‘OTE.’ This ‘high-input, high-pollution, low-efficiency’ profile is unsustainable.
- Agriculture and ecology-oriented profile: The polygon approximates a balanced, pentagonal shape shifted toward high ‘OTE’ and ‘NDVI.’ This represents the ‘high-output, low-pressure’ model, which aligns with the Sustainable Development Goals.
- Integrated service profile: The polygon shows moderate values across all dimensions, with a noticeable ‘OTE’ deficit relative to its ‘NDVI’. This suggests that service-oriented towns can leverage green infrastructure and intelligent management to close their efficiency gap.

4.5 Policy implications and AI-informed optimisation pathways

Building on the granular diagnostics from Sections 4.2–4.4, this section translates the identified inefficiencies into concrete, actionable policy targets for each township. The goal is to bridge the gap between analytical insight and practical governance by defining a clear, algorithmically-derived pathway for improvement and proposing a dynamic framework for its implementation. The core results are synthesised in Figure 3.

The slack variables from the SBM-DEA model provide the exact magnitude of improvement required for each inefficient township to reach the efficiency frontier. These quantified targets are visualised in Figure 3(A), revealing a clear, three-tiered priority structure directly linked to the development typology established in Section 4.4.

Tier 1 High-priority industrial transformation (ZhiDian, LiuFu, FuJing)

The industry-driven townships require the most substantial interventions. ZhiDian, as the least efficient unit, faces the most demanding targets: a 32.0% reduction in energy consumption, an 18.5% reduction in PM2.5 concentration, and a 15.0% increase in NDVI. This confirms that the county’s core sustainability challenge lies in decarbonising and cleaning up its industrial and port operations. Policy here must focus on mandatory technological upgrades, strict emission standards, and a shift towards circular economy practices.

Tier 2 Moderate improvement in service hubs (HuaiDian, ZhaoDeYing, ZhouYing)

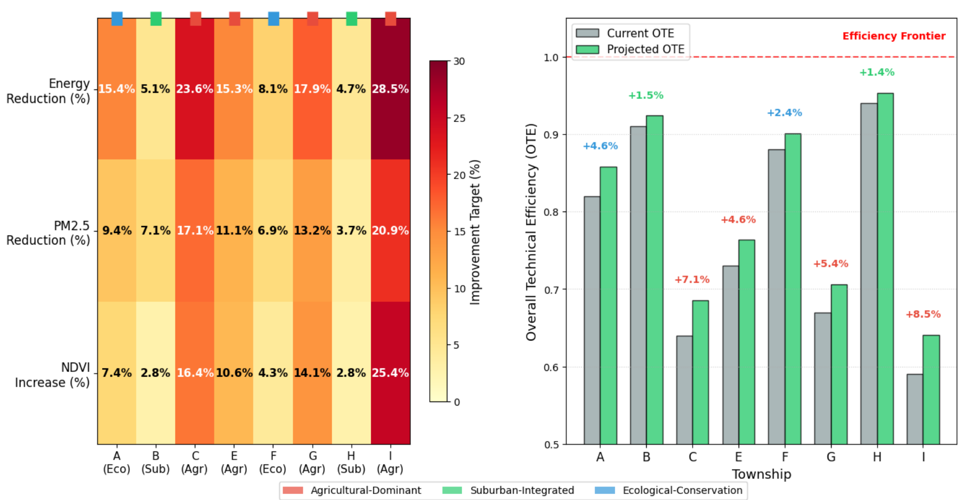
Integrated Service townships set moderate targets, primarily focused on improving energy efficiency (8%–10% reduction) and air quality (6%–8% reduction in PM2.5), with transportation and building management as key areas. This suggests that innovative city solutions – such as intelligent traffic systems, building energy management, and green public infrastructure – are the key levers for these areas.

Tier 3 Enhancement of agricultural and ecological systems (LiuZhuangDian, LaoCheng)

Agriculture and ecology-oriented townships have the most modest targets, primarily focused on marginal increases in vegetation cover and maintaining already good air quality. Policy should support conservation, adoption of precision agriculture, and sustainable ecotourism to solidify their role as the county's ecological foundation.

This targeted approach ensures that limited fiscal and administrative resources are allocated precisely where they will have the most significant impact on the county's overall ecological efficiency.

Figure 3 Quantification results after optimisation, (a) township-specific optimisation targets (derived from AI-enhanced DEA slack analysis) (b) current vs. project OTE after optimisation with AI-informed policy implementation (see online version for colours)



(a) (b)

The potential impact of implementing these tailored interventions is quantified in Figure 3(b), which compares current OTE scores with projected scores post-optimisation. The analysis indicates that with full target achievement, six of the eight inefficient townships could reach the efficiency frontier (OTE = 1.0), while the remaining two would achieve near-frontier status. The county-wide average OTE would rise by approximately 17.5%, with the most dramatic gain projected for ZhiDian Township (a potential +72.4% increase from OTE = 0.58 to 1.00).

To operationalise these targets, we propose an AI-enhanced dynamic governance framework, depicted as a closed-loop cycle in Figure 3. This framework moves beyond static planning to enable adaptive, responsive management:

- Continuous AI monitoring: The loop initiates with the real-time acquisition of NDVI (via satellite) and PM2.5 data (via IoT sensors), providing the 'ground truth' feed.

- Periodic AI-DEA diagnosis: This data, integrated with updated socioeconomic inputs, feeds into the periodic AI-enhanced DEA model, which recalculates efficiency scores and slack variables to diagnose new or persistent bottlenecks.
- Precision policy design: The diagnostic outputs inform the (re)design of highly localised interventions. For instance, the model might prescribe AI-optimised fertiliser schedules for LiuZhuangDian or real-time pollution source apportionment and control for ZhiDian.
- Local implementation and enforcement: Policies are implemented by local authorities, supported by AI tools that improve compliance monitoring and effectiveness.
- Performance feedback and adaptation: New monitoring data is fed back into the model, closing the loop. This enables continuous tracking of progress, evaluation of policy effectiveness, and adaptive adjustment of targets and strategies, creating a learning governance system.

Finally, to ensure the successful adoption of this technically complex framework, we propose bridging the techno-social divide through transparent communication and participatory governance. The algorithmically-derived metrics from Figure 3 should be translated into accessible 'township ecological health dashboards' for public dissemination. For example, ZhiDian's residents could track real-time progress toward its 18.5% reduction in PM2.5. By making performance data visible, relatable, and linked to local quality of life, citizens can be transformed from passive observers into active stakeholders and partners in sustainability, fostering accountability and collaborative action between the government, businesses, and the community.

5 Conclusions

This study demonstrates that integrating AI with non-parametric SBM-DEA models offers a robust framework for advancing local ecological governance. Applying this AI-enhanced approach to Shenqiu County reveals a stark contrast in development pathways: industry-driven towns exhibit low efficiency (mean OTE = 0.62), characterised by high energy use and PM2.5 pollution, whereas agriculture and ecology-oriented towns achieve high efficiency by maximising green cover with modest inputs. The research contributes methodologically by combining AI-driven data processing with Slack-based DEA to pinpoint inefficiency sources, and practically by translating findings into quantified optimisation targets and proposing an AI-enhanced dynamic governance framework for adaptive policymaking. In agricultural regions like Shenqiu, sustainability may depend more on modernising agriculture and strengthening the environment than on expanding polluting industry. Future research could scale this approach, integrate real-time AI prediction, and examine socioeconomic barriers to implementation. This study provides a scalable blueprint for leveraging AI to balance economic development with ecological preservation.

Declarations

There are no potential conflicts of interest in my paper.

The datasets generated and analysed during this study are available from the corresponding author on reasonable request. Publicly available or referenced datasets include: Sentinel-2 satellite imagery (for NDVI reference), air quality data from The Weather Company platforms, and macroeconomic aggregates from the Shenqiu County Government Statistical Bulletin (2025).

The author has agreed to publish the paper.

References

AlNaimat, S., Ismail, U.M., Ibrahim, A.I. et al. (2024) 'Machine learning modeling and statistical optimization of dye removal from contaminated water using CTAB-functionalized graphene oxide', *Water, Air, & Soil Pollution*, Vol. 235, No. 10, pp.671–688.

Athwal, N., Wells, V.K., Carrigan, M. and Henninger, C.E. (2019) 'Sustainable luxury marketing: a synthesis and research agenda', *International Journal of Management Reviews*, Vol. 21, No. 4, pp.405–426.

Cugurullo, F. (2018) 'Exposing smart cities and eco-cities: Frankenstein urbanism and the sustainability challenges of the experimental city', *Environment and Planning A: Economy and Space*, Vol. 50, No. 1, pp.73–92.

Dauvergne, P. (2022) 'Is artificial intelligence greening global supply chains? Exposing the political economy of environmental costs', *Review of International Political Economy*, Vol. 29, No. 3, pp.696–718.

Demirel, P. and Kesidou, E. (2019) 'Sustainability-oriented capabilities for eco-innovation: meeting the regulatory, technology, and market demands', *Business Strategy and the Environment*, Vol. 28, No. 5, pp.847–857.

Hall, C.M. (2019) 'Constructing sustainable tourism development: the 2030 agenda and the managerial ecology of sustainable tourism', *Journal of Sustainable Tourism*, Vol. 27, No. 7, pp.1044–1060.

Hickel, J. (2019) 'The contradiction of the sustainable development goals: growth versus ecology on a finite planet', *Sustainable Development*, Vol. 27, No. 5, pp.873–884.

Kumar, A., Kumar, J. and Bhaskar, T. (2020) 'Utilization of lignin: a sustainable and eco-friendly approach', *Journal of the Energy Institute*, Vol. 93, No. 1, pp.235–271.

Manikandan, S., Kaviya, R.S., Shreeharan, D.H. et al. (2025) 'Artificial intelligence-driven sustainability: enhancing carbon capture for sustainable development goals – a review', *Sustainable Development*, Vol. 33, No. 2, pp.2004–2029.

Mariotti, N., Bonomo, M., Fagiolari, L., Barbero, N., Gerbaldi, C., Bella, F. et al. (2020) 'Recent advances in eco-friendly and cost-effective materials towards sustainable dye-sensitized solar cells', *Green Chemistry*, Vol. 22, No. 21, pp.7168–7218.

Oliveira, J.L.d., Santos, F.A.d., Pereira, A.E.S., Pasquoto, T., Lima, R., Grillo, R. et al. (2018) 'Zein nanoparticles as eco-friendly carrier systems for botanical repellents aiming sustainable agriculture', *Journal of Agricultural and Food Chemistry*, Vol. 66, No. 6, pp.1330–1340.

Panwar, A., Olfati, M., Pant, M. et al. (2022) 'A review on the 40 years of existence of data envelopment analysis models: historic development and current trends', *Archives of Computational Methods in Engineering*, Vol. 29, No. 7, pp.5397–5413.

Polasky, S., Kling, C.L., Levin, S.A., Carpenter, S.R., Ehrlich, P.R., Daily, G.C. et al. (2019) 'Role of economics in analyzing the environment and sustainable development', *Proceedings of the National Academy of Sciences*, Vol. 116, No. 12, pp.5233–5238.

Sanders, N.R., Boone, T., Ganeshan, R. and Wood, J.D. (2019) 'Sustainable supply chains in the age of AI and digitization: research challenges and opportunities', *Journal of Business Logistics*, Vol. 40, No. 3, pp.229–240.

Wang, Q., Li, Y. and Li, R. (2024) 'Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (AI)', *Humanities and Social Sciences Communications*, Vol. 11, No. 1, pp.1–18.

Yaseen, K.O.J., Lee, J. et al. (2023) 'Automatic sequential stitching of high-resolution panorama for android devices using precapture feature detection and the orientation sensor', *Sensors*, Vol. 23, No. 2, pp.879–891.

Yazdi, M., Mohammadpour, J., Li, H. et al. (2023) 'Fault tree analysis improvements: a bibliometric analysis and literature review', *Quality and Reliability Engineering International*, Vol. 39, No. 5, pp.1639–1659.