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Assessing the eco-efficiency of industrial parks recycling transformation: Evidence from data envelopment analysis (DEA) and fuzzy set qualitative comparative analysis (fsQCA)

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Industrial parks are essential for promoting regional economic development, yet their linear growth model has become unsustainable. Hence, implementing the industrial park recycling transformation (IPRT) is necessary and urgent. However, the current literature on IPRT performance evaluation and improvement has not kept up with practical developments. This study aims to evaluate the eco-efficiency of IPRT and identify the variables and configurations that affect its enhancement. To achieve this, the authors employed super-efficiency data envelopment analysis and fuzzy set qualitative comparative analysis to analyze data collected from 21 IPRT demonstration pilot parks. Drawing on the Technology-Organization-Environment framework, this study identified three configurations with high eco-efficiency and two configurations with non-high eco-efficiency for IPRT. The findings indicate that eco-efficiency varies significantly among different parks and is the result of multiple factors and interactions, with environmental supervision playing a pivotal role. Additionally, the results suggest that the local economic development level and the technological capacity of parks are substitutable. Parks in regions with modest economies tend to focus on environment-technology-oriented transformations, while external factors drive IPRT of parks in areas with developed economies. These findings offer guidance for parks to adopt appropriate strategy profiles and provide policy options for governments.

KEYWORDS

eco-efficiency, data envelopment analysis, fuzzy set qualitative comparative analysis, industrial parks, recycling transformation

1 Introduction

Industrial parks have become an essential element for nurturing emerging industries, promoting urbanization, boosting regional economic development, and strengthening the global supply chain. However, despite their significant contribution to economic output, industrial parks also have a significant impact on resource consumption and environmental pollution (Mathews et al., 2018). In this context, Industrial Park Recycling Transformation (hereafter referred to as IPRT) has emerged as a crucial strategy. IPRT is an integrated system aimed at minimizing resource consumption and environmental pollution, which enhances land and resource productivity, promotes waste recycling, and reduces energy and water consumption. Practical experience has shown that IPRT, by enhancing resource recovery and reducing emissions, contributes to the development of a circular economy (CE) (Winans et al., 2017). However, theoretical research on IPRT has yet to keep up with practical progress due to the complexity of explanatory mechanisms, which include both inputs and outputs.

China boasts the largest number of industrial parks worldwide, which have played a pivotal role in propelling the country's economy. However, the traditional linear growth model characterized by intensive resource consumption and severe pollution has rendered this development model unsustainable (Feng and Yan, 2007; Mathews and Tan, 2016). To address this issue and maximize the economic and environmental benefits of industrial parks, China has implemented a series of top-down initiatives to promote circularity, including the implementation of IPRT. Since 2012, IPRT has been incorporated into the national CE project, with seven batches of pilot projects covering 129 industrial parks across the country launched by two national ministries from 2012 to 2017. By 2020, 69 parks had been approved for IPRT, leading to a reduction of around 350 million tons of carbon emissions. These achievements have fueled further efforts. In the "Carbon Peak Action Plan" unveiled in 2020, China pledged to further cut emissions, with IPRT playing a critical role in achieving these targets.

Previous literature on CE has predominantly focused on institutional or corporate factors, with only limited attention paid to factors at the industrial park level (Mathews et al., 2018). Existing research on industrial parks has mainly centered on eco-industrial parks (EIPs), rather than IPRTs, which have been identified as a critical strategy to achieve industrial sustainability (Zhu et al., 2015). While some scholars have addressed the performance evaluation of IPRTs, a comprehensive evaluation based on ecological efficiency is still lacking, and the evaluation methods need to be strengthened (Zhu et al., 2015). Moreover, research on mechanisms for improving IPRT performance tends to consider individual factors separately, failing to reflect the integration of elements and the complex interactions within the mechanism (Murray et al., 2017; Tang and Liao, 2021). Additionally, existing research methods primarily analyze the impact of a single factor on IPRT performance (Neves et al., 2020), but fail to address the complex pathways required for effectively improving eco-efficiency. Therefore, given the complexity of explanatory factors and mechanisms, it is timely and critical to focus on the performance evaluation of IPRTs and their improvement methods.

Therefore, the author has chosen China as the research context and adopted an analytical framework that covers an integration perspective and different factors, based on the super-efficiency data envelopment analysis (DEA) model and fuzzy-set qualitative comparative analysis (fsQCA), to explain the factors and mechanisms that lead to different levels of eco-efficiency in IPRTs. The authors aim to answer two key research questions: 1) What is the eco-efficiency level of each IPRT park? and 2) What are the variables and configurations that affect the improvement of IPRT eco-efficiency?

This study provides two main contributions to the existing literature. Firstly, it adopts an integrated and configurational perspective to characterize the concurrent and equifinal factors that affect IPRT eco-efficiency. The findings suggest that multiple factors drive the improvement paths of IPRT eco-efficiency through three equivalent approaches. Additionally, the study highlights the critical role of environmental factors in enhancing eco-efficiency and the presence of a substitutable relationship between multiple factors. Secondly, the study employs the TOE framework to elucidate the intricate causality underlying the efforts to enhance IPRT eco-efficiency, with a focus on technological, organizational, and environmental factors. These contributions address the research gaps in the existing literature, which has predominantly centered on identifying the role of a single factor and overlooked the complex and multifaceted mechanisms that drive IPRT. The findings can inform policymakers and managers of industrial parks on how to improve eco-efficiency in IPRTs by taking an integrated and holistic approach.

2 Literature review

In Section 2, the authors review the extant literature on IPRT evaluation and factors influencing IPRT performance in terms of the theoretical, methodological, and practical evolution and voids, thus highlighting the necessity and significance of this research.

2.1 Evaluation of industrial park recycling transformation

The increasing focus on sustainable development has prompted a greater interest in evaluating the effectiveness of CE initiatives. This has led to research on the economic benefits of firms participating in CE practices (Chertow and Lombardi, 2005), as well as on the role of eco-industrial parks (EIPs) in local economic and social spheres (Paquin et al., 2015). However, research on measuring sustainability achieved in IPRT is still in its early stages, and the evaluation methods currently employed are limited.

Some scholars have used life cycle analysis to study environmental outputs of IPRT such as CO_2 and NOx (Grant et al., 2010; van Capelleveen et al., 2018). Although methods such as DEA, entropy weight method, analytical hierarchy process (AHP), emergy, and multi-agent systems have been widely used in eco-efficiency measurements, they have hardly been applied in IPRT performance evaluations in complex input-output scenarios. While a few studies have used the concept of eco-efficiency to evaluate the performance of industrial parks (Liu et al., 2015; Martín Gómez et al., 2018), the literature on evaluating the eco-efficiency of IPRT is notably deficient compared to that of EIP research.

Typically, existing studies employ indicators such as resource productivity, energy productivity, and environmental performance, which fail to systematically reflect the intricate material flows and cannot accurately evaluate outcomes with multiple inputs and outputs. As noted by Yang et al. (2022), IPRT is a complex transformation that involves political, social, and economic factors. Consequently, a more comprehensive and systematic approach is required to assess the eco-efficiency of IPRT practices and investigate the complex mechanisms involved (Jessop and Sum, 2000).

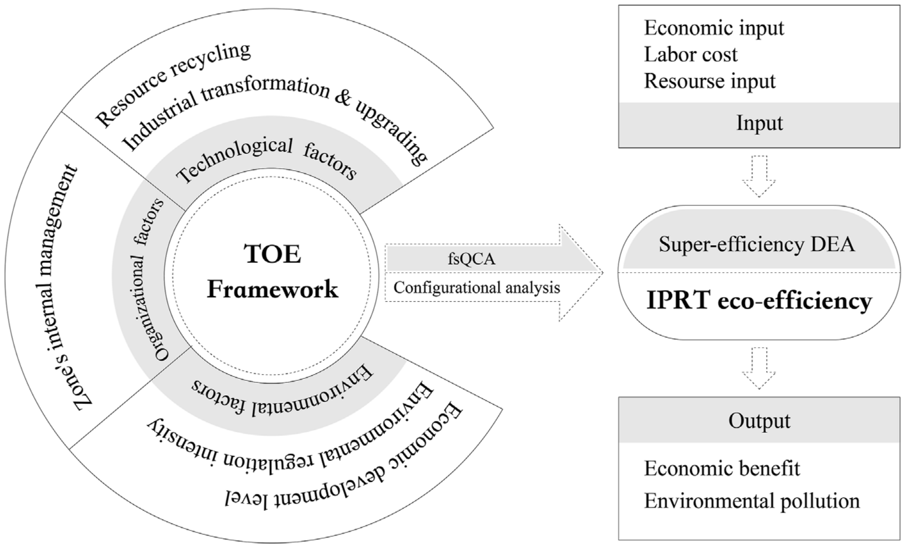

FIGURE 1
Research process of the study.

2.2 Factors influencing IPRT performance

The existing literature on the eco-efficiency of industrial parks has mainly focused on examining the role of individual factors. Previous studies have used quantitative methods such as Pearson correlation analysis and the Tobit model to determine the relationship between independent variables and eco-efficiency. These studies have found that factors such as tourism development (Peng et al., 2017), industrial structure (Cook and Seiford, 2009), and technological capacity (Suchek et al., 2021) can enhance eco-efficiency, while investment driven by profitability (Hu et al., 2019) can harm it. However, these methods often treat independent variables separately and assume their impact on dependent variables are linear and cumulative (Li et al., 2021).

In reality, IPRT eco-efficiency is a complex non-linear system that depends on interactions among various factors (Ribeiro et al., 2018; Reuter et al., 2019). Studies using the contingency perspective have mainly focused on a single factor (Mathews and Tan, 2011), and research methods employed in prior studies could not provide further insights into factor interactions (Taddeo et al., 2012; Dai et al., 2022). As a result, the existing literature has led to unsatisfactory conclusions (Genc et al., 2019; Panchal et al., 2021). To improve eco-performance research, it is recommended to incorporate elements from organizational management and the external environment, recognizing that factors collectively impact eco-efficiency rather than in isolation (Neves et al., 2020).

The integration perspective provides a more nuanced understanding of the complex causality of how IPRT eco-efficiency can be influenced compared to the contingency prism. However, the current literature has yet to explore the complex configurational features and the interplay of multiple factors. Additionally, quantitative methods such as the Tobit model or the stochastic frontier approach (SFA) often treat independent variables as separate entities and assume their impact on dependent variables is linear and cumulative (Li et al., 2021). Therefore, there is a pressing need to combine quantitative and qualitative analyses to address research gaps and investigate the interactive influence of multiple factors on IPRT eco-efficiency (Lo et al., 2020).

3 Model formulation

This section introduces the research models and variables used in the study, followed by an exposition on the data sources, with a focus on the 21 IPRT demonstration pilot industrial parks as the research sample. In light of the study's intricate and multi-level design, we provide Figure 1 to present the research process.

3.1 Methodology

In Section 3.1, we describe the methodology used to evaluate the eco-efficiency of IPRT and the configurational analysis of factors influencing it. Two methods were employed: the input-oriented super-efficiency DEA model and fuzzy set qualitative comparative analysis.

3.1.1 Super-efficiency DEA model

The DEA model was utilized to calculate and rank the eco-efficiency of the IPRT demonstration pilot parks. This non-parametric method has received considerable attention in prior literature (Charnes et al., 1978; Mardani et al., 2017). Typically, multiple decision-making units (DMUs) appear simultaneously in the production frontier. However, traditional DEA models only distinguish between effective and ineffective DMUs and do not evaluate the effective ones further. Andersen and Peterson. (1993) proposed an input-oriented super-efficiency DEA model to address this limitation, which excludes the DMU_i from the frontier when efficiency analysis is performed for the ith DMU, enabling a complete ranking of all DMUs.

In this study, the two outputs of environmental pollution and economic benefit pursued inconsistent goals, while the input elements aimed to minimize the same goal (Amara et al., 2020). Therefore, the authors opted for the input-oriented super-efficiency DEA model. Additionally, since the input and output factors included environmental considerations, the constant returns to scale (CRS) models were unsuitable for this research (Buzzigoli et al., 2010). Thus, the variable returns to scale (VRS) model was used, which is as follows:

$$Min\,\theta - \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)$$

$$s.t.\begin{cases} \sum\limits_{\substack{j=1 \\ j\neq o}}^{n} x_{ij}\lambda_j + S_i^- = \theta x_{io}, i = 1,\ldots,m, \\ \sum\limits_{\substack{j=1 \\ j\neq o}}^{n} y_{rj}\lambda_j - S_r^+ = y_{ro}, r = 1,\ldots,s, \\ \lambda_j \geq 0, j = 1,\ldots,n, j \neq o, \\ S_i^-, S_r^+ \geq 0, \forall i, r. \end{cases}$$

Where x and y denote input and output variables; S_i^- and S_r^+ refer to the input and output slack variables, respectively; λ_j is the multiplier of the effective DMU; ε is the non-archimedean infinitesimal; j≠o means that the super-efficiency DEA model will remove the DMUo being evaluated from the reference set. θ represents the super-efficiency value. A DMU will be considered efficient when θ ≥ 1; otherwise, inefficient.

3.1.2 Fuzzy set qualitative comparative analysis

As a qualitative comparative analysis (QCA) method based on set theory, fuzzy-set qualitative comparative analysis (fsQCA) is an analytical technique that utilizes Boolean algebra to conceptualize the antecedents and outcomes of a study as binary values (0–1) (Ragin, 2008; Meuer and Fiss, 2020). This method explores the joint effect resulting from the interplay of multiple factors in some instances. In this study, the authors employed fsQCA to capture the impact of configurations composed of different factors on IPRT eco-efficiency. The decision was based on three main reasons. Firstly, the net effect analysis of technological, organizational, or environmental factors alone cannot fully interpret the complex causality that influences eco-efficiency. In contrast, fsQCA can tap into the joint effects of multiple factors from a more integrated perspective, reflecting the idea that all roads lead to Rome (Wagemann et al., 2016). Secondly, fsQCA can identify multiple interaction effects characterized by conjunction, equifinality, and causal asymmetry of multiple factors (Fiss, 2011; Kumar et al., 2022). Finally, fsQCA has less stringent sample size requirements compared to econometric analysis methods, while still requiring a sample size that outnumbers the model(s) in case studies (Gupta et al., 2020).

In fsQCA, variables are first calibrated, followed by a necessity analysis on individual conditions, and then a sufficiency analysis on the configurations (Ragin, 2008). From a set theory perspective, necessity analysis checks whether the set of outcomes is a subset of a specific set of conditions. When certain conditions always lead to the outcome, the conditions will be considered necessary. Configurational analysis aims to test whether the configurations of different factors are both necessary and sufficient for specific outcomes. From a set theory perspective, the authors need to examine whether the set represented by the structure composed of multiple conditions is a subset of the outcome set.

3.2 Variables and measurement

Section 3.2 describes the dependent and independent variables used in the study. The dependent variables consist of eco-efficiency values obtained through the super-efficiency DEA model and comprise a set of input and output indicators. The independent variables are selected at the technological, organizational, and environmental levels to identify the conditional variables that make up the configurations.

3.2.1 Dependent variables

The dependent variables analyzed in this study are the eco-efficiency values of each park, which are obtained using the super-efficiency DEA model and comprise a set of input and output indicators. This model has been widely applied in various fields and provides a comprehensive performance evaluation, as indicated by Fan et al. (2017). To identify the critical input and output factors of typical industrial parks involved in IPRT, the authors conducted a thorough review of prior literature and consulted with experts, as reported by Liu et al. (2015). Subsequently, the authors selected three input and four output indicators to construct the evaluation system, which encompasses three dimensions: resources, environment, and economy. Specifically, the output indicators represent economic output (a desirable outcome) and environmental pollution (an undesirable outcome), while the input indicators include traditional inputs and resource consumption.

3.2.1.1 Input indicators

The literature on efficiency evaluation in other fields has traditionally utilized capital and human resources as input variables (Cook and Seiford, 2009). However, given the emphasis on ecological benefits in the context of IPRT, the authors have included resource consumption as an additional input variable in the evaluation system. In doing so, the IPRT input variables consist of two traditional inputs as well as resources. Specifically, the economic input was calculated as the sum of the park's annual fixed asset investment and research and development (R&D) expenses, while the human resource cost was measured by the annual average of employees in the park. Resource input was measured by the park's total annual energy consumption, which encompasses the park's total annual consumption of coal, oil, and natural gas.

3.2.1.2 Output indicators

To account for the impact of output on ecological benefit, the authors included environmental pollution as one of the outputs in the evaluation system. As such, the outputs considered in this study comprised both desirable and undesirable outcomes. Specifically, the former mainly referred to economic benefit, which was measured by the park's annual gross product, while the latter represented environmental pollution. To measure environmental pollution, the authors used typical pollutants such as sulfur dioxide (SO_2) emissions, organic wastewater emissions, and solid waste output to represent air pollution, wastewater emission, and solid waste generated in the parks, respectively. It is worth noting that in the DEA model, the output indicators should be as significant as possible. However, CE aims to maximize desirable output while minimizing undesirable output. Therefore, it was necessary to transform the undesirable output in this study. To achieve this, the authors used the monotonic decreasing transformation method, which has been previously applied in CE evaluations (Seiford and Zhu, 2002; Vencheh et al., 2005; Hua et al., 2008).

3.2.2 Independent variables

As previously mentioned, this study adopted a three-level approach to identify the conditional variables that make up the configurations (Sun et al., 2020; Ullah et al., 2021). The TOE framework is a generalized and comprehensive model, with the specific referents of T, O, and E varying depending on the research context and field. Consequently, it is essential for scholars to tailor the framework to their specific scenarios (Baker, 2012). In this study, the authors selected resource recycling (RR) and industrial transformation and upgrading (ITU) at the technological level, Zone's internal management (ZIM) at the organizational level, and economic development level (EDL) and environmental regulation intensity (ERI) at the environmental level as the five conditional variables constituting the dependent variables.

3.2.2.1 Technological factors

Resource recycling (RR) refers to the practice of reusing wastewater and recycling solid waste in IPRT (Geng et al., 2007). In this study, resource recycling was measured by the industrial wastewater reuse rate, which is calculated as the amount of water recycled by water equipment divided by the total amount of water used in production (Wang et al., 2021). This is because water resource input and utilization are essential for all parks, regardless of their type.

Industrial transformation and upgrading (ITU) refers to a firm's competitive edge in market and resource sharing, the creation of specialized affiliated industries, and technology spillover. To measure the focal park's industrial transformation and upgrading, the degree of CE industrial linkage was chosen. Scholars have observed that a sustainable industrial network based on the CE model and industrial symbiosis logic in the supply chain is conducive to circular utilization and minimizing resource consumption. The degree of CE industrial linkage was calculated by dividing the total output value of firms in the CE industrial chain by the industrial park GDP. This concept of industrial linkage draws from the idea of a food chain in an ecological community, where scholars have examined biological community linkages since the 1980s.

3.2.2.2 Organizational factors

Zone's internal management (ZIM) plays a vital role in facilitating industrial parks' transition to a circular economy. Effective internal management will be conducive to IPRT. It facilitates the transformation to a circular economy. By fully unleashing the potential of industrial parks, it will eventually improve the eco-efficiency of the parks (Chembessi et al., 2022). The internal management effectiveness can be manifested in promoting the parks' internal infrastructure construction and information-based transformation (Hong and Gasparatos, 2020). Given the role in reflecting internal management effectiveness (Zhu et al., 2015), the authors selected the rate of completion and compliance of major projects as a proxy indicator of the ZIM.

3.2.2.3 Environmental factors

Economic development level (EDL) can be indicated by GDP, *per capita* income, and economic growth rate (Chong and Olesen, 2017; Ofterdinger et al., 2021). A higher economic development level measured by GDP means a more solid material basis to underpin IPRT and propel CE development (Liu et al., 2015). Therefore, the authors chose local GDP to describe the EDL.

Environmental regulation intensity (ERI) is another critical factor for industrial parks' circularization efforts. Government regulation can help solve environmental problems and compensate for market failures (Porter and Linde, 1995). ERI not only reflects local governments' attentiveness to circular economy development but also closely relates to technological innovation and ZIM improvement (Zhu et al., 2021). To measure ERI, the authors used energy consumption per unit of GDP, which indicates the energy utilization in economic activities within the parks and the intensity of local environmental supervision and inspection. The calculation involved dividing total energy consumption by the GDP of the industrial parks, lagging it by one period, and subtracting the result from 1 to obtain ERI.

3.3 Data sources

The IPRT was introduced as a major demonstration pilot CE project in China's 12th Five-Year Plan for National Economy and Society Development (2011–2015). Following this plan, many provinces and cities in China began to promote the demonstration pilot IPRT projects. Among these, Jiangsu province was a forerunner with notable enlightenment in IPRT implementation for its peers, and the demonstration pilot IPRT parks in Jiangsu province of China were chosen as the sample for this study. The IPRT of 36 industrial parks was approved by the Jiangsu Provincial Development and Reform Commission, and the authors of this study selected 21 of these parks after removing samples with missing data. The primary data for this study were obtained from assessment reports and supplemented by information from the Economic Development Bureau, Environmental Protection Bureau, Land and Resource Bureau Branch, and statistical yearbooks of China.

4 Numerical results and analysis

Section 4 commences with an assessment of the eco-efficiency of the IPRT, followed by the identification of potential avenues for enhancing its eco-efficiency through configurational analysis. The authors further substantiate the findings by conducting a comprehensive robustness test.

TABLE 1 Eco-efficiency of the demonstration pilot industrial parks (2012–2015).

Name of the industrial parks	Abbreviation	2012	2013	2014	2015	Mean
Binjiang Economic Development Zone	Z1	0.752	0.664	0.604	1.032	0.763
Zhonglou Economic development Zone	Z2	0.948	1.017	1.033	1.159	1.039
Changzhou Hi-Tech Industrial Development Zone	Z3	0.959	0.966	1.026	1.034	0.996
Suzhou Economic Development Zone	Z4	1.081	1.040	1.020	1.097	1.060
Shuyang Economic and Technological Development Zone	Z5	0.158	0.187	0.224	0.255	0.206
Suqian Economic and Technological Development Zone	Z6	0.633	0.636	0.591	0.553	0.603
Pizhou Economic Development Zone	Z7	0.481	0.336	0.338	0.343	0.374
Xinyi Economic development Zone	Z8	0.893	0.868	1.121	1.015	0.974
Dantu Economic Development Zone	Z9	0.603	0.636	1.044	1.015	0.825
Huishan Economic Development Zone	Z10	0.678	1.050	1.045	1.004	0.944
Yixing Environmental Protection Technology Industrial Park	Z11	0.412	0.366	0.422	0.412	0.403
Jihu Economic Development Zone	Z12	0.267	0.223	0.171	0.149	0.202
Hongze Economic Development Zone	Z13	0.212	0.213	0.208	0.215	0.212
Nanjing Binjiang Economic Development Zone	Z14	1.044	1.014	0.912	1.063	1.008
Lishui Development Zone	Z15	0.544	0.566	1.037	1.056	0.801
Nantong Economic and Technological Development Zone	Z16	0.536	0.562	0.587	0.601	0.571
Taizhou Gaogang Hi-Tech Industrial Development Zone	Z17	1.017	1.037	1.028	1.009	1.023
Taizhou Medical and Pharmaceutical Hi-Tech Development Zone	Z18	1.004	1.003	1.010	1.058	1.019
Dongtai Economic Development Zone	Z19	0.254	0.392	0.573	0.822	0.510
Yancheng Economic and Technological Development Zone	Z20	0.144	0.168	1.010	0.305	0.407
Suzhou Industrial Park	Z21	0.860	0.867	0.890	0.917	0.884

4.1 Eco-efficiency evaluation

To effectively rank and conduct a comparative analysis in both time and spatial dimensions, the authors used EMS (Version 1.3) to measure the eco-efficiency of the demonstration pilot industrial parks in China (Table 1). The results are as follows.

The analysis above indicates a steady increase in eco-efficiency of IPRT across all parks from 2012 to 2015. However, the parks exhibit considerable variation in average eco-efficiency values, leading to their classification into three categories: high, medium, and low. High eco-efficiency parks, namely, Z4, Z2, Z17, Z18, and Z14, have an average value greater than 1.0, while medium eco-efficiency parks (Z3, Z8, Z10, Z21, Z15, Z9, and Z1) have an average value between 0.7 and 1.0. Low eco-efficiency parks (Z6, Z16, Z19, Z7, Z11, Z20, Z12, Z13, and Z5) have an average value between 0.1 and 0.7.

Z4 and Z2, established in 2002 and beginning IPRT in 2012, have achieved impressive CE growth through effective use of geographic resources and high economic development levels. Z14, in Nanjing, has achieved high eco-efficiency through significant economic and technological transformations. Z17 and Z18 have focused on developing high-end medical devices and new materials industries, respectively, transforming traditional industries into higher quality and more efficient high-end industries. In contrast, Z5, Z6, and Z7 have low eco-efficiency due to severe pollution from their coal chemical and energy industries, requiring immediate attention to reduce waste and gas emissions. Z19 and Z20 have experienced fluctuations in eco-efficiency, but improvements have been made after implementing IPRT. Z16 and Z11 can improve their eco-efficiency by leveraging their geographic location and optimizing their resources.

4.2 Configurational analysis of eco-efficiency

This subsection describes the configurational analysis of eco-efficiency in the study. It includes the calibration of variables using the direct method, necessity analysis, sufficiency configurations with varying consistency and coverage using fsQCA 3.0, and a robustness test with adjusted consistency level and anchor points thresholds.

4.2.1 Calibration of variables and necessity analysis

This study used the direct method of variable calibration following previous research (Witt et al., 2022). Calibration is required to transform raw data into set membership scores ranging from 0 to 1. In this research, the authors first specified the three anchor points: fully in, crossover point, and fully out of

TABLE 2 Variable calibrations and descriptions.

Variables	Fully in	Crossover point	Fully out	Mean	Std. D	Min	Max
EE	0.996	0.801	0.407	0.706	0.301	0.202	1.060
RR	90.473	88.500	80.550	85.317	8.418	63.868	95.500
ITU	53.725	47.500	34.813	46.900	16.910	20.000	93.490
ZIM	100.000	89.951	50.000	89.951	16.386	44.444	100.000
EDL	5,369.523	4,626.450	3,078.020	4,914.020	2,942.907	1831.000	13,894.000
ERI	0.458	0.335	0.223	0.404	0.337	0.048	1.630

TABLE 3 Results of necessity analysis.

Conditions	High eco-efficiency		Non-high eco-efficiency	
	Consistency	Coverage	Consistency	Coverage
RR	0.600	0.576	0.530	0.495
~RR	0.474	0.510	0.546	0.570
ITU	0.446	0.459	0.589	0.589
~ITU	0.601	0.601	0.459	0.446
ZIM	0.808	0.583	0.702	0.492
~ZIM	0.296	0.506	0.405	0.672
EDL	0.502	0.578	0.430	0.481
~EDL	0.549	0.498	0.623	0.549
ERI	0.800	0.812	0.321	0.316
~ERI	0.327	0.331	0.810	0.797

four conditional and one outcome variables except for ZIM, using the 25th, 50th, and 75th percentiles in the sample values. Then, the distribution of ZIM shows a notable right-skewed feature with values representing 100% major project completion and compliance rate. Hence, the authors set the three anchor points: fully in, crossover point, and fully out of the variable, using the fifth, mean, and 95th percentiles. Moreover, the authors replaced the conditional values calibrated to 0.5 with 0.501, as a value of 0.5 would be automatically removed (Leppänen et al., 2023). Table 2 presents the calibration values and descriptions of each variable.

The authors employed fsQCA 3.0 to conduct a necessity analysis, with consistency and coverage being the two main metric results (Zheng et al., 2021). Table 3 illustrates the consistency levels of all conditions leading to high or non-high eco-efficiency. Results show that no single variable constitutes a necessary condition for achieving high eco-efficiency or avoiding non-high eco-efficiency. Instead, multiple conditional variables must interact and match to enhance the eco-efficiency of IPRT.

4.2.2 Sufficiency configurations

The sufficiency analysis examined various combinations of multiple conditional variables, evaluated by consistency and frequency thresholds. To meet best QCA application practices (Schneider and Wagemann, 2012), while acknowledging that different thresholds may be used in different research contexts (Fainshmidt et al., 2022; Hartmann et al., 2022), the authors set the consistency threshold to 0.8 and the frequency threshold to 1. To avoid inappropriate counterfactual analysis due to the lack of consensus on the relationships between five conditional variables and eco-efficiency, the authors set the causal condition as "present or absent" and used fsQCA 3.0 to produce three types of solutions with varying complexity (Amara et al., 2020). The authors identified conditional configurations by comparing intermediate and parsimonious solutions in a nested manner, drawing on the extant literature (Ding and Wu, 2022).

Table 4 presents diverse configurations that result in high or non-high eco-efficiency. Each column represents a unique configuration, and the consistency and coverage of both single and overall solutions surpass the threshold, indicating that the findings are valid. Among these configurations, four (M1, M2, M3a, and M3b) lead to high eco-efficiency, with M3a and M3b sharing core conditions (EDL*ERI) and, hence, forming a second-order equivalent configuration. The overall solution reveals that 90.4% of industrial parks achieve relatively high IPRT eco-efficiency, and all three equifinal solution paths together account for 60.3% of

TABLE 4 Results of configurational analysis.

Conditions		High eco-efficiency				Non-high eco-efficiency		
		M1	M2	M3a	M3b	M4a	M4b	M5
T	RR	⊗	•	•		⊗	⊗	
	ITU		●		⊗	•		●
O	ZIM	•	⊗	•	•		•	⊗
E	EDL	⊗	⊗	●	●		⊗	•
	ERI	●	●	●	●	⊗	⊗	⊗
Consistency		0.837	0.987	0.931	0.981	0.922	0.935	0.948
Raw Coverage		0.313	0.279	0.114	0.243	0.377	0.263	0.245
Unique Coverage		0.161	0.101	0.081	0.017	0.157	0.146	0.118
Solution Coverage		0.603				0.641		
Overall Consistency		0.904				0.953		

Note: Following the outcome reporting format proposed by Ragin. (2008), black circles ("●") indicate the presence of a condition, and circles with a cross-out ("⊗") indicate its absence. Moreover, large circles indicate core conditions, and small circles refer to peripheral conditions.

cases with high eco-efficiency. The authors then provide detailed explanations of the main configurations, with reference to Furnari et al. (2021).

4.2.2.1 Configurational analysis of conditions leading to high eco-efficiency

M1 (~RR*ZIM*~EDL*ERI) indicates that industrial parks located in regions with a modest EDL, high ERI, and weak RR can still achieve high eco-efficiency with effective ZIM is ensured. RR (T) and ERI (E) are the core conditions, while ZIM (O) and EDL (E) play complementary roles. In response to strict environmental regulations, these parks tend to shift their focus towards resource recycling and improving internal management, rather than solely relying on outcome-oriented technologies. This configuration covers two samples and can explain about 31% of the cases with high IPRT eco-efficiency.

M2 (RR*ITU*~ZIM*~EDL*ERI) suggests that parks in regions with low EDL, weak ZIM, and high ERI can achieve high eco-efficiency through the benefits of ITU and RR. The core conditions are ITU (T) and ERI (E), while other factors play supportive roles. In response to stringent environmental regulations, such parks are inclined to prioritize ITUs to strengthen the CE industrial chain and inter-industrial linkage, promoting IPRT. M2 covers one case with a unique coverage of 0.101. This configuration can account for approximately 28% of the cases with high IPRT eco-efficiency.

M3 (ZIM*EDL*ERI) indicates that industrial parks in regions with high ERI and EDL can achieve high eco-efficiency if a sound ZIM is in place. EDL (E) and ERI (E) are the core, while ZIM (O) plays a supporting role. It means that parks may utilize the significantly-favorable external environment to compensate for internal management and technology deficiency. This configuration has the highest coverage, explaining approximately 36% of the cases with high IPRT eco-efficiency.

A comparison of M1, M2, and M3 reveals that ERI is a common factor in all configurations that trigger high eco-efficiency, and serves as the core condition in conjunction with either economic development level (E) or technology (T). The importance of ERI, as a major external factor, in enhancing IPRT is highlighted. In contrast, ZIM only plays a supporting role. Furthermore, parks' technological capacity and EDL are interchangeable. Parks in economically disadvantaged areas tend to focus on process-oriented ITU or abandon outcome-oriented resource recycling technology, both of which are conducive to high eco-efficiency and demonstrate environment-plus-technology-driven characteristics. In regions with relatively high EDL, technological capacity is no longer the core factor for achieving high eco-efficiency. Parks with complementary conditions, including ERI and EDL, will also achieve high eco-efficiency, but this pattern is mainly driven by external environmental factors.

4.2.2.2 Configurational analysis of non-high eco-efficiency conditions

M4 (~RR*~ERI) suggests that low ERI in industrial parks, combined with inadequate RR, will lead to non-high eco-efficiency. RR (T) and ERI (E) are the core conditions. It indicates that IPRT driven by outcome-oriented resource recycling technologies without an effective environmental regulation will also meet Waterloo in realizing an ideal goal. This configuration covers five samples and explains about 38% of the cases.

M5 (ITU*~ZIM*EDL*~ERI) indicates that industrial parks with a weak ERI and ZIM may achieve non-high eco-efficiency despite having a high EDL and sound ITU. ZIM and ERI are the core conditions, supported by ITU and EDL. Parks may struggle to achieve their desired outcomes in IPRT if internal management and environmental regulation are not improved. This configuration covers three samples and explains about 51% of the cases.

The comparison of M4 and M5 reveals that insufficient environmental regulation (~ERI) occurs in both configurations leading to non-high eco-efficiency. It indicates that the absence of environmental review will impede IPRT. Besides, among all the configurations triggering non-high eco-efficiency, the park's

TABLE 5 Results of configurational analysis with an enhanced consistency level.

Conditions		High eco-efficiency				Non-high eco-efficiency		
		M1a	M1	M2a	M2b	M3a	M3b	M4
T	RR	⊗	•	•		⊗	⊗	
	ITU	●	●		⊗	●		●
O	ZIM	•	⊗	•	•		•	⊗
E	EDL	⊗	⊗	●	●		⊗	•
	ERI	●	●	●	●	⊗	⊗	⊗
Consistency		0.871	0.931	0.987	0.981	0.922	0.935	0.948
Raw Coverage		0.076	0.114	0.279	0.243	0.377	0.263	0.245
Unique Coverage		0.047	0.081	0.100	0.073	0.157	0.146	0.118
Solution Coverage		0.490				0.641		
Overall Consistency		0.972				0.953		

TABLE 6 Results of Configurational Analysis with new Calibration Anchor Points Thresholds.

Conditions		High eco-efficiency				Non-high eco-efficiency		
		M1	M2	M3a	M3b	M4a	M4b	M4c
T	RR	⊗	•	•		⊗		
	ITU		●		⊗	●	⊗	●
O	ZIM	•	⊗	•	•		•	
E	EDL	⊗	⊗	●	●		⊗	•
	ERI	●	●	●	●	⊗	⊗	⊗
Consistency		0.854	0.961	0.945	0.955	0.922	0.800	0.856
Raw Coverage		0.442	0.216	0.390	0.357	0.450	0.371	0.431
Unique Coverage		0.147	0.084	0.050	0.003	0.089	0.199	0.088
Solution Coverage		0.681				0.758		
Overall Consistency		0.895				0.830		

technological conditions and organizational factors are substitutable. Concretely, low ERI, the disregard for outcome-oriented technologies such as RR, or the disappointing ZIM will all lead to lower IPRT performance. Based on those mentioned above, the lack of ERI alone does not directly lead to the failure; parks' unsatisfactory IPRT eco-efficiency is also the result of sluggish technological conditions or organizational capacity.

4.2.3 Robustness test

Echoing Skaaning's (2011) suggestions, the authors conducted a robustness test from two aspects. First, the consistency level was adjusted by redefining the consistency level of single condition necessity analysis and configurational sufficiency analysis from 0.8 to 0.85 (Cui et al., 2017; Chen et al., 2021). The results of the adjusted configurational analysis are presented in Table 5. In line with the work by Fiss. (2011), the authors set the three anchor points thresholds: fully in, crossover point, and fully out of the outcome and conditional variables except for ZIM using 95%, 50%, and 5% percentiles. For ZIM, the authors retained the former anchor points. The findings are presented in Table 6. Additionally, the authors evaluated the robustness of the results using the two criteria proposed by Schneider and Wagemann. (2012). Overall, the study's findings are reliable and robust.

5 Conclusion

In Section 5, the authors provide a comprehensive conclusion to the paper, encompassing the study's theoretical and practical contributions. Additionally, we provide a policy-making and discussion subsection, highlighting the implications of the findings for decision-makers. Finally, the authors propose future research avenues to expand upon the current study's insights.

5.1 Conclusion and discussion

Drawing on panel data collected from 21 IPRT demonstration pilot industrial parks between 2012 and 2015, this study employs the super-efficiency DEA model to evaluate and analyze IPRT eco-efficiency. Subsequently, the TOE framework is utilized to identify three distinct paths for promoting IPRT through fsQCA. Notably, these paths underscore two noteworthy features: firstly, achieving a common objective is feasible through different means, and secondly, multiple paths can coexist simultaneously.

Specifically, this paper makes two contributions to the existing literature. Firstly, the study characterizes the factors that influence eco-efficiency as being concurrent and equifinal. As suggested by Rihoux and Ragin. (2009), the "configurational perspective" effectively comprehends complex causality. The research findings indicate that a single factor cannot be deemed necessary or sufficient in constituting a path that leads to high eco-efficiency. Each path to promote eco-efficiency comprises multiple concurrent factors. Moreover, multiple factors drive the improvement of eco-efficiency through three equivalent approaches. Additionally, the study reveals that a substitutable relationship exists between the multiple factors, and environmental factors are crucial in enhancing IPRT eco-efficiency. These findings are a novel attempt to explain the IPRT enhancement paths from an integrated perspective using configurational analysis (Li et al., 2021).

Secondly, the study employs the TOE framework to explain the complex causality underlying the work to enhance IPRT eco-efficiency. While existing literature acknowledges the mechanisms through which IPRT performance can be affected, most studies have focused on identifying the role of a single factor, ignoring the critical and complex mechanisms that drive transformation. As noted by Kristensen and Mosgaard. (2020), most indicators in research on circular economy concentrate on economic benefits, and social, governmental, and environmental factors receive less attention. Neves et al. (2020) also highlighted these limitations and suggested that future research incorporate factors that influence EIP performance, such as organizational management and external environmental factors. To address this gap, the authors selected dependent variables related to technological, organizational, and environmental aspects to explain causal relationships using the well-established TOE framework. The study finds that parks in regions with modest economic development prefer the route characterized by notable "environment plus technology" features, whereas those in regions with a booming economy are more likely to undergo an environment-oriented transformation.

5.2 Implications for policy-making

The results of this study have significant implications for government officials tasked with the development of industrial parks with IPRT practices. Firstly, this study presents evidence that achieving eco-efficiency in industrial parks requires a multifaceted approach. Policymakers should therefore acknowledge that no single factor can be deemed necessary or sufficient in achieving high eco-efficiency, and thus implement policies that promote the coordination of multiple factors, including technological, organizational, and environmental aspects (Luo and Leipold, 2022). This could be achieved through financial incentives, technical assistance, and training programs to assist parks in identifying and implementing eco-efficient practices (Zhu et al., 2021).

Secondly, the study suggests that different paths may be followed to enhance eco-efficiency in industrial parks, depending on the local economic development level. In regions with modest economic development, industrial parks should focus on technological and environmental factors, whereas those in regions with a booming economy should prioritize environmental factors. Policymakers must consider these regional differences when designing policies to support the development of IPRT.

Finally, the study emphasizes the crucial role of local governments in promoting IPRT. Local governments should guide industrial parks in adopting suitable paths in line with their technological capacity and organizational characteristics. Additionally, they should provide targeted public services and policies that support the development of eco-efficient industrial parks, including environmental protection review and supervision, technical assistance, and training programs (Ghisellini et al., 2016; Suchek et al., 2021).

5.3 Avenues for future research

The findings also provide valuable avenues for future research. First, some may criticize that the use of samples from a single province could potentially make the findings less generalizable. Therefore, future research could collect samples from various sources and types to enrich the arguments and uncover new paths for improving IPRT eco-efficiency.

Apart from that, the authors drew on the TOE framework to analyze the factors influencing IPRT eco-efficiency and took technological (T), organizational (O), and environmental (E) factors as the antecedent combination of conditions. However, it must be acknowledged that the factors affecting IPRT performance are complex and diverse, indicating that some other effective paths are yet to be explored (Chembessi et al., 2022). For instance, the TOE framework does not fully consider the micro-level factors inside the industrial parks (Zhu et al., 2015; Sun et al., 2020), which calls for further explorations.

In closing, the authors selected 2012–2015 as the observation interval; hence, the statistics are not up-to-date. This is because the data were obtained from reports on the IPRT demonstration pilot industrial parks evaluation organized by Jiangsu province of China. Since then, no such evaluation has been conducted. Thus, the statistics in this study did not include the latest data after 2016.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

All authors contributed to the study's conception and design. Material preparation, data collection, analysis, manuscript draft, and revision were performed by ZL and JW. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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