Assessing Circularity and Sustainability in Eco-Innovation Parks: A Novel Approach for Optimizing SME Contributions

CHAU NGUYEN, University of Twente, The Netherlands

The shift from a traditional linear economy to a circular economy (CE) aims to reduce environmental impact while fostering sustainability and economic growth is a promising concept. Eco-innovation parks (EIPs) have adopted these principles by forming Industrial Symbiosis networks through collaboration in environmental and resource efficiencies management to improve environmental and economic performance. Although SMEs play a critical role in these hubs due to their agility, adaptability, innovation capability, and contribution to the employment and economic landscape, evaluating their impact on the development and effectiveness of these parks still remains a complex challenge. In this research, quantitative analysis methods, including binary logistic regression and Data Envelopment Analysis (DEA), are employed to investigate the influence of sustainability indicators on the development of effective eco-innovation parks, particularly concentrating on the role of SMEs within these parks. This study then aims to identify patterns of efficiency within eco-innovation parks by assessing their performance and comparing the characteristics of efficient and inefficient regions. The findings from three developed scenarios show that the presence of SMEs and their economic contributions positively influence the likelihood of legislation and policy actions that facilitate the development of eco-innovation parks. Moreover, the results highlight how a combination of eco-activities can optimize the emergence of success indicators within the parks. By examining these efficiency patterns, the findings emphasize the importance of standardized environmental management practices, efficient inter-firm collaboration and government facilitation in the park's effectiveness. This analysis provides a helpful reference for policymakers to develop standardized assessment frameworks and improve the performance of less efficient regions.

Additional Key Words and Phrases: circular economy; data envelopment analysis; eco-innovation parks; SMEs; binary logistic regression; institutional strategies

1 INTRODUCTION

Closed-loop systems view waste as a valuable resource, help businesses reduce their dependency on external sources, save material costs, and thus strengthen resource security. In this setting, since 2015, the European Commission has implemented two Circular Economy Action Plans (CEAPs) to stimulate the transition towards this new model [2]. SMEs are believed to be critical enablers of sustainable regional development due to their capability in advanced resource efficiency implementation, including the design of sustainable products, recycling initiatives, and investments in innovative waste management practices [51]. Given that the Circular Economy (CE) functions on multiple levels—within individual companies, between businesses, and via interactions with consumers—it is therefore challenging for SMEs to implement it on their own due to limited resources, knowledge, and capital [42]. While SMEs are instrumental in innovation park development and other CE initiatives, the role of SMEs within clusters is under-explored, primarily due to the dominance of larger industries in these clusters.

Research on SMEs, EIPs, and CE shows a prevalence in regional and national circular economy performance assessment, sustainability indicators examination, and cluster dynamic formation. Researchers adopt a macro-level perspective of CE analysis [4, 8], focusing on countries and regions, or a micro-level approach regarding the operational process and management within a business [27, 51] or a meso-level approach [15], referring to hubs for circularity or eco-innovation parks. In the meso-level context, most studies focus on either productivity efficiency or eco-efficiency of eco-innovation parks, without mentioning the presence of SMEs.

Although many studies have indicated that SMEs could achieve superior environmental performance through the adoption of CE practices, the same level of achievement is not guaranteed for economic and social outcomes [52]. This research uses quantitative methods to analyze the dataset from an international survey on eco-innovation parks [29] to examine the combined effects of eight groups of sustainability initiatives on the performance of eco-innovation parks. These sectors include energy management (energy efficiency and renewable energy sources), waste management, water management, material flow, environmental conservation and protection (biodiversity, air pollution prevention, noise prevention, land use), mobility and transportation, environmental management systems, and cultural, social, health, and safety aspects [29]. The influence of these indicators, along with the presence of SMEs within the parks, is analyzed to understand their contribution to the parks' success.

[29] constructed eight success factors to assess the effective development of eco-innovation parks. The presence of these success indicators within the parks measures their effective development and management across six comprehensive areas: economic viability (economic value added, economic activity diversity), policy (policy & regulation frameworks, financial incentives), organization and setups, scientific and technological cooperation, geographical and infrastructure factors, and marketing and communication [29]. This study, based on the constructed framework, explores the influence of sustainability initiatives on the occurrence of these success indicators in parks. These indicators encompass both meso and macro levels, incorporating regional programs and policy actions that have direct impacts on the meso scale. The inclusion of cultural, social, health, safety, and economic viability as variables in the analysis reflects the important role of the organization's environmental culture and the capital availability of eco-parks in the adoption of CE practices [42]. Thus, the main research question of this study is:

What role do SMEs play in the development of effective eco-innovation parks (EIPs), considering the interplay between sustainability and CE concepts? This can be answered through the following sub-research questions:

(1) How do sustainability indicators along with the presence of SMEs, influence the efficiency of eco-innovation parks?
(2) What characteristics define efficiency within eco-innovation parks, and how do these characteristics vary between efficient and inefficient regions according to DEA analysis?
(3) What common patterns or practices in terms of sustainability initiatives and local policy strategies are identified among efficient regions that could be leveraged to inspire improvements in less efficient areas?

A review by [40] on methods used in cluster performance analysis reveals that case studies are the most frequently employed approach due to their in-depth, descriptive, and specific nature. This research fills the gap by employing Data Envelopment Analysis (DEA), a non-parametric method, to evaluate circular economy (CE) efficiency at the

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meso-level. Eco-innovation parks are treated as Decision Making Units (DMUs), with those on the efficiency frontier serving as benchmarks for the inefficient ones. These benchmarks, representing actual eco-parks with real data, are associated with best practices, providing helpful reference sets for patterns and areas needing improvement identification. In addition, a binary regression model was selected to examine the impact of eco-criteria implementation in the parks on the presence or absence of success factors. The findings will serve as insights for policy recommendations to address inefficient areas, enhance the CE ecosystem and assist SMEs in realizing the benefits of the transition.

The structure of this paper is as follows: Section 2 provides a review of the relevant literature on the topic. Section 3 describes in detail the methodologies employed in the study, including binary logistics regression and the DEA BCC model. Section 4 outlines the experimental framework design and setup. Section 5 presents a comprehensive analysis of the results and discusses their implications, offering policy recommendations to leverage inefficient regions. The final section provides the conclusion and suggestion.

2 LITERATURE REVIEW

Scientific research has made comprehensive efforts to define the concept of the circular economy (CE), considering three dimensions of sustainable development: economic, environmental, and social [25]. To date, there have been many studies assessing the efficiency of eco-innovation parks or evaluate cluster performance, particularly in China, often followed by policy recommendations to address areas of inefficiency [15, 18, 57]. [40] proposed a framework for evaluating cluster performance regarding its transition to a circular economy (CE), which includes four key components: intercommunication, financial resources, human resources, and marketing activities or [44] identified six key areas that influence the success and limitations of eco-innovation parks: (i) symbiotic business relationships, (ii) economic value added, (iii) awareness and information sharing, (iv) policy and regulatory frameworks, (v) organizational and institutional setups, and (vi) technical factors. However, according to [56], there still remains an absence of a unified framework for evaluating CE practices in innovation parks. Sustainability indicators play an important role in the efficiency of eco-innovation parks. A case study in Taiwan showed that waste recovery and reuse helped increase the overall eco-efficiency of an innovation park by 30-40% [23]. Studies [14, 18] both emphasize the importance of indicators such as land and water consumption, energy and industrial structure as well as industrial added value in enhancing eco-efficiency. [56] extends this by introducing a new dimension for evaluating circular economy efficiency, which highlights the relationship between resources and environmental performance, emphasizing the role of GDP and leading industries as driving factors.

2.1 SMEs in Industrial Symbiosis network

In terms of the Industrial Symbiosis (IS) network, a study by [28] extended the existing assessment of the IS network by reviewing the environmental and socio-economic impacts of a developing network on the west coast of Sweden. In terms of the relationship between SMEs and clusters, [40] gave a comprehensive literature review suggesting that cluster serves as a critical enabler for SMEs in the transition to a CE, which supports and creates an environment for SMEs to engage in CE practices through cluster's performance development. However, these researches have not explored how SMEs contribute to cluster performance through IS networks within a CE context.

2.2 SMEs in transition towards CE practices

Several researchers have looked into the barriers SMEs face when adopting CE practices. [27] and [42] found out that the key barriers SMEs face in the transition towards a CE are a lack of support from supply and demand networks and insufficient capital. Results from [49] indicate that a balanced combination of soft and hard initiatives targeting specific segments and stakeholders could accelerate the market approval of circular products and increase the competitive strength of SMEs adopting eco-efficiency actions. The findings emphasize the importance of institutional intervention in reducing administrative procedures and organizational bureaucracy barriers.

2.3 Frameworks and methodologies for assessing eco-industrial park performance in the concept of circular economy

Several frameworks and techniques have been proposed to assess the performance of industrial parks and their shift towards a circular economy, such as case study, correlation-regression analysis, lifecycle assessment, material flow analysis, DEA or Multi-Criteria Decision-Making (MCDM) [40]. Among them, DEA-based models are one of the most frequently implemented benchmarking methods for assessing sustainability and eco-operation efficiency [32], allowing the measurement and ranking of DMUs' effectiveness based on multiple input indicators and output indicators [23] without relying on the assumptions of relationships between them. Therefore, DEA provides a robust framework for policymakers to establish realistic and achievable targets aimed at enhancing circular economy practices in different regions [26]. Similarly, regression analysis is a significant statistical method utilized within cluster analysis frameworks to identify the best fitting set of indicators for assessing sustainability levels across various domains and regions [3, 58]. Binary logistic regression, used specifically when the response variable can only take two possible values (yes or no) [43], is frequently employed in clinical prediction models to classify, explain, or predict the values of certain characteristics, behaviors, or outcomes. [36, 46].

3 METHODOLOGIES

This section will discuss in detail the methods used in this study, including the application of binary logistic regression to analyze the impact of eco-criteria on a set of success factors, the Data Envelopment Analysis (DEA), Banker, Charnes, and Cooper (BCC) Model to assess the efficiency of eco-innovation parks, and the mean statistical method to summarize the data. These models were performed using various data analytics software packages including Pycharm, Excel, pyDEA and JMP.

3.1 Binary logistics regression

The logistic regression model is primarily applied when the dependent variable is categorical. Its underlying principles are rooted in probabilities and the properties of the logistic curve [22], wherein the log odds of the outcome are predicted as a linear combination of the predictor variables. This study employs a binary logistic regression model to assess the collective impact of eco and sub-eco criteria activities within parks on eight distinct success factors. The list of independent and dependent variables is specified in Table 1. These success factors collectively assess the successful development and operation of eco-innovation parks.

Given the binary nature of the dependent variables, this model helps predicts the presence or absence of success factors based on a set of eco-activities conducted by the park. While conventional Ordinary Least Squares (OLS) regression can also be utilized to model binary variables through linear probability models, it may produce predicted values that fall outside the (0, 1) range and violate normal distribution and homogeneous error variance assumptions [37], justifying the use of logistic regression in this research. The assumptions required for the validity of the binary logistic regression model are mentioned in various sources [19, 21, 48, 53]. Generally, the model relies on three core assumptions: (1) observations must be independent, (2) perfect multicollinearity among independent variables must be absent, and (3) continuous predictors must be linearly related to a transformed version of the outcome, indicating linearity in the logit [21].

Given the large number of eco and sub-eco criteria presented in the dataset relative to the small sample size (N = 129), the events per variable (EPV) rule was considered when selecting candidate predictors to examine their impact on the success factors. EPV refers to the ratio of the number of observations to the number of degrees of freedom (parameters) required to represent the predictors when constructing the model [55]. According to [34], the concept of EPV $\geq$ 10 is deemed acceptable for both logistic regression and cox regression. Although recent studies suggest that the EPV $\geq$ 10 criterion may be too stringent in certain circumstances [30], lower EPV values in prediction model development are frequently linked to poorer predictive performance [20, 47]. Hence, in this study, an EPV $\geq$10 was employed to determine the maximum number of eco and sub-eco criteria examined for their influence on the presence of SMEs and the park's success factors.

Moreover, due to the binary nature of the response variables, this research proposes to use Cohen's Kappa coefficient alongside R-Square (U) to assess the association or agreement between classifications of two predictors on a nominal scale. Cohen's Kappa coefficient is appropriate as it examines the actual agreement of the measurement, correcting for random agreement [9, 50]. The results will aid in refining the set of predictors before constructing the Binary Logistic Model.

3.2 DEA Banker, Charnes, and Cooper model

The literature review underscores that Data Envelopment Analysis (DEA) is a robust quantitative benchmarking method widely and effectively used to identify, compare, and optimize the efficiency of similar units within an organization or between organizations [39]. Even when the selected inputs and outputs do not precisely measure the means consumed and results achieved, as typically related to production theory, they are categorized based on performance measures. In other words, inputs usually fall under the "less-the-better" type of performance measures, while outputs fall under the "more-the-better" type [11]. [5] extended the earlier work of [7] to account for variable returns to scale (VRS). In this research, the BCC model was used, which suggests that changes (reduction or increase) in a Decision-Making Unit's (DMU) inputs do not lead to proportional changes in its outputs.

The BCC model can distinguish between technical and scale inefficiencies by estimating pure technical efficiency at a given scale of operation [1]. Additionally, since each eco-park differs in size, operates in different environments, and does not operate at an optimal scale, which lead to variable efficiencies, the BCC model is favorable in this context. An output-oriented DEA model, which maximizes outputs given a fixed level of input, is selected as this research aims to understand how much a park can enhance its success level while consuming a given level of resources, thereby identifying potential areas for improvement.

3.3 Mean statistics to assess efficiency scores and practices

After calculating the efficiency scores, the parks are classified into efficient and inefficient regions, allowing for the identification of patterns and the comparison of practices between them. To analyze the results of the innovation parks based on these categories, mean statistics are used due to the extensive range of eco and sub-eco criteria (12 eco criteria, 8 of which have sub-eco criteria) and a set of 8 predefined success factors [29]. This approach helps in understanding the relative differences between the efficient and inefficient groups in three main areas: (1) input and output factors, (2) performance in each success sector, and (3) characteristics of eco-activities implemented in the parks. The results are visualized through bar charts, effectively illustrating the disparities between these regions.

The analysis focuses on primary attributes shared among the most referenced efficient parks by the inefficient ones to draw lessons from their practices. Based on the outcome of the analysis, optimal strategies, and policy intervention are suggested. Paying attention to more influential factors or examining the sharing characteristics of efficient groups may help to identify best practices.

4 EXPERIMENTAL SET-UP

4.1 Experimental framework

The research framework consists of four stages. The first stage involves data gathering, evaluating dataset completeness, and addressing any missing values. The second stage focuses on the main analysis, assessing the impact of eco and sub-eco criteria, as well as the presence of SMEs, on the efficiency of the parks using binary logistic regression, and evaluating the technical efficiency of these parks through the DEA BCC model. In the third stage, statistical methods are utilized to identify patterns and compare characteristics between efficient and inefficient areas. The final stage involves proposing policy strategies and institutional interventions to support the adoption of sustainability practices and improve the efficiency of inefficient groups.

4.2 Dataset

This study examines the dataset from the international survey on eco-innovation parks published in 2014 by the Swiss Federal Office for the Environment (FOEN) [29]. Conducted within the framework of ECO-INNOVERA, the survey included 168 European and non-European innovation parks implementing eco-innovation or industrial symbioses. Each park is characterized by 78 attributes, including general information, eco-criteria, sub-eco-criteria, and success factors. The parks' environmental activities are defined by twelve eco-criteria, with eight having sub-eco-criteria specifying the actions undertaken. Additionally, eight predefined success factors are used to identify the successful development and operation of eco-innovation parks.

Due to the lack of SME information in the original survey and the scarcity of SME data within eco-industrial parks, this study retrieved additional data on SMEs at the country level from the "Country SME Key Figures 2023" report [12], based on structural business statistics (SBS) published by Eurostat. This data covers the 'non-financial business economy' (NACE Rev. 2) of EU-27 member states [10]. The study used value added at factor cost (million Euros) and the number of enterprises as economic indicators for the year 2014, aligning with the survey publication period.

Since the SME key figures cover only EU-27 member states, data for non-European countries (Australia, Israel, Japan, South Korea, United States) were retrieved from the Annual Enterprise Statistics by Size Class for Special Aggregates of NACE Rev.2 Activities, relying on the OECD Structural business statistics by size class and economic activity [1] (all Eurostat). The advantage of using Eurostat data is that the statistics are harmonised and comparable across countries. Two countries, India and China, were excluded from the impact analysis due to insufficient

[1] Oecd. (n.d.). SDBS structural business statistics (ISIC rev. 4). https://stats.oecd.org/Index.aspx?DataSetCode=SSIS$_BSC_ISIC4$

information. Additionally, urban parks and parks in the planning stages were removed from the dataset.

Due to the scarcity of information about the presence and performance of SMEs within the parks, three scenarios were developed to assess the presence of SMEs on the park's efficiency. The first scenario assumed that the number of SMEs within the eco-innovation parks approximates the number of companies there, based on the estimation by the World Trade Organization [2] that SMEs constitute more than 90% of the overall business demographic. The second and third scenarios retrieved data about the number of SMEs and value added by SMEs at factor cost on a country level from external sources mentioned above. These attributes were examined individually and in combination with a set of sustainability indicators of the park to determine the role of SMEs in developing effective eco-innovation parks under the convergence of CE practices and sustainability indicators.

4.3 Set up and Preprocessing

4.3.1 Data analytics approach for binary logistics regression model. Regarding predictor selection, as mentioned in Section 3.1, the EPV ≥ 10 criterion was used to establish both the minimum sample size and the maximum number of potential predictors. After checking the data distribution and removing outliers, 129 observations remained, leading to the selection of 10 predictors for the model. A script was executed to calculate the R-Square (U) and Kappa coefficients for all combinations of non-empty binary columns to understand the agreement between binary predictors. Predictors with high R-Square (U) values and low Kappa values were preferred due to their stronger relationship with the outcome and provision of unique information, minimizing multicollinearity and redundancy. Since the R-Square (U) and Kappa values of all predictors were very low (mostly under 0.2), the area under the curve (AUC) were employed to evaluate the logistic regression model, and the results were compared between models. The refined list of eco criteria used as predictors to construct the Binary Logistics Model is shown in Table 1.

The first assumption of the binary logistic model, which requires that each observation in the dataset is independent of the others, is satisfied based on the dataset collection information provided in [29]. To check the multicollinearity assumption, the Variance Inflation Factor (VIF) was used to measure how much the variance of the coefficient estimate is being inflated by multicollinearity. Values of VIF exceeding 10 indicates increased multicollinearity, which can lead to unstable estimates of regression coefficients, overinflated standard errors, and compromised model fit indices [24, 45]. All variables have very small VIF values, implying no multicollinearity issues.

The Variance Inflation Factor (VIF) is given by the formula Eq .1:

$$\mathrm{VIF}_i = \frac{1}{1 - R_i^2} \tag{1}$$

where:

- R_i^2 is the coefficient of determination of the regression that predicts the i-th predictor as a function of the remaining predictors.

The last assumption requires a linear relationship between continuous independent variables and the log-odds of the predicted probabilities for the success factors [21]. After running the model, the probability formula is saved as shown in Eq. 2

$$\text{Probability} = \frac{1}{1 + e^{-(\text{Intercept}+\text{Coefficient}_1 \times X_1 + \text{Coefficient}_2 \times X_2 + \ldots)}} \tag{2}$$

[2]WTO, 2016. World Trade Report 2016. Levelling the trading field for SMEs.https://www.wto.org/english/res_e/publications_e/wtr16_e.htm.

Then, the logit (log-odds) of the predicted probabilities are calculated based on Eq.3

$$\text{Logit} = \ln\left(\frac{\text{Probability}}{1 - \text{Probability}}\right) \tag{3}$$

In the following step, a scatter plot is created with each continuous predictor (number of SMEs in the hub, number of SMEs at the country level, and value added by SMEs) on the x-axis and the log-odds of the success factor occurrence probability on the y-axis. Given that the linear trendline represents the linear relationship between the predictors and success factors, if the Loess curve significantly deviates from the line, the linearity assumption fails [21]. Observation from Figure 1 shows that these two lines are relatively close, demonstrating that the linearity assumption is met.

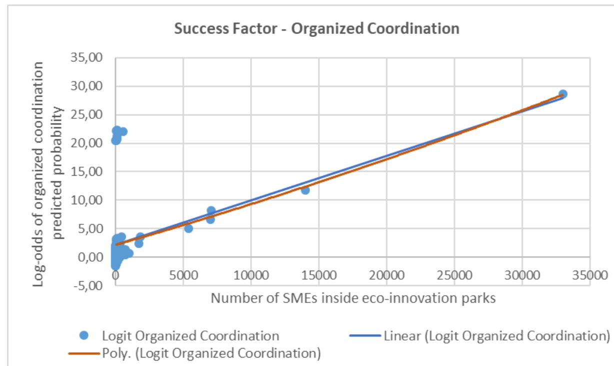

Fig. 1. Checking the linearity assumption.

Sensitivity and specificity are measures used to assess the reliability of logistic regression model. The Receiver Operating Characteristic (ROC) curve depicts the true positive rate (sensitivity) versus the false positive rate (1 - specificity), as detailed in [16]. The accuracy of the test is greater when the ROC curve approaches the upper corner of the graph. Ideally, an optimal ROC curve will yield an Area Under the Curve (AUC) of 1. According to [31], an AUC greater than 0.5 is required for a valid model. In this experiment, the AUC of the defined predictors for each success factor is above 0.67 (Table 2), indicating that the model has fair diagnostic performance overall.

4.3.2 Data analytics approach for DEA BCC model. The DEA model mandates specific criteria regarding the number of indicators to maintain the rationality of computations. Various guidelines exist regarding the selection of inputs and outputs based on the number of DMUs to maintain the DEA models' discriminatory power. [13] recommend that the number of Decision Making Units (DMUs) should be no less than double the combined total of input and output variables to ensure the model's effectiveness. However, both [17] and [38] suggest a higher threshold, recommending that the number of DMUs should be at least three times the combined count of inputs and outputs to secure sufficient discrimination capability. Based on the performance measures outlined by [11], this study uses the Size of Park (ha) and the Number of Companies as inputs, and the Number of Jobs, Sum of Eco Criteria, Sum of Sub Eco Criteria, and Sum of Success Factors as outputs. With 72 DMUs, the selected input and output factors meet these guidelines.

To eliminate correlated input and output factors, a heat map of Pearson correlation coefficients (r) for all indicators (Figure 2) was analyzed. Most input-output pairs show very low correlation, except for a strong positive relationship between the Sum of Eco Criteria and Sum of Sub Eco Criteria (r = 0.91). This is because these two predictors consist of almost

Table 1. Sustainability Indicators as Inputs and Success Factors as Outputs of Binary Logistics Regression model.

Input Factors	**Output Factors**
AP/Air Monitoring	Cooperation with Science and Technology Institutions
CSH/Social	Organized Coordination
LO/Land Use Optimization	Local Diversity of Economic Activities
WTM/Water Use Efficiency	Financial Incentives
Mobility/Transportation	Clear Designation as an Eco-Innovation Park
EE/CHP Plant	Location and Regional Infrastructure
RE/Energy Management	Policy and Regulation Frameworks
EE/Energy Efficient Building	Economic Value Added
WM/Recycling	

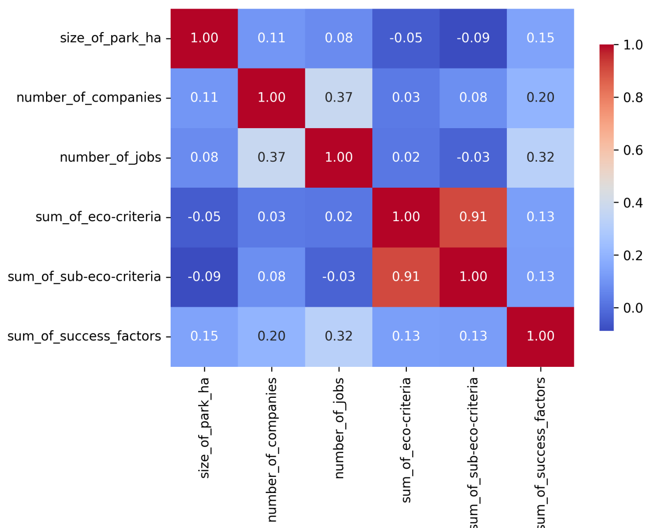

Fig. 2. Pearson correlation coefficients of DEA inputs and outputs.

the same elements; eco-criteria include sub-eco criteria, although some do not have sub-categories. Therefore, both are not excluded to ensure a comprehensive comparison of all eco-activities between regions.

Due to the significant imbalance in data magnitudes between input and output factors, such as the Sum of Sub-Eco Criteria, Sum of Eco Criteria and the Size of Park (ha), mean normalization is applied to reduce this imbalance.

The mean value for column i (an input or output) is calculated using Eq. 4:

$$\bar{V_i} = \frac{1}{N} \sum_{n=1}^{N} V_{ni} \tag{4}$$

where:

- $\bar{V_i}$ is the mean value for column i.
- N is the number of DMUs.
- V_{ni} is the value of DMU n for a given input or output i.

To normalize the values, Eq. 5 is used:

$$V_{Norm_{ni}} = \frac{V_{ni}}{\bar{V_i}} \tag{5}$$

where $V_{Norm_{ni}}$ is the normalized value for the value associated with DMU n and input or output in column i.

5 RESULTS AND DISCUSSION

5.1 On answering sub RQ 1 - Impact analysis

The result presented in Table 2 summarizes key metrics of significant predictors for eight success indicators of the parks, along with the AUC (Area Under the Curve) of each model. The predictors are presented in the table with two key metrics: p-values and odds ratios with a 95% confidence interval (CI). Unit odds ratios are used when assessing the number of SMEs within the parks, while range odds ratios are applied when assessing the number of SMEs and the value added by SMEs at the country level. This approach is necessary because these two independent variables have a very large scale, making a one-unit change too small to capture significant effects.

Overall, based on the AUC and lack-of-fit test, the model shows poor discrimination for the clear designation of eco-innovation parks and for location and regional infrastructure. However, for the remaining success indicators, the model performs fairly well in classification tasks.

A brief analysis of the results from Table 2 shows that the presence of social and educational promotion within the park significantly increases the likelihood of success in financial incentives (scenarios 2 and 3) and policy and regulation frameworks (scenario 1) by approximately three times. Social and educational initiatives refer to programs that enhance equity, community engagement, and educational opportunities within the park. A study by [6] also emphasizes the need for more education for sustainability in the business world, shifting the motivation for adopting eco-innovation from standards compliance to sustainable goals. Moreover, the presence of efficient and eco-friendly transportation substantially influences the organizational and institutional setups of inter-firm collaborations. The odds of success in organized coordination are approximately five times higher in the presence of such transportation systems.

The results also reveals that recycling and energy management significantly impact financial incentives across all three scenarios, increasing the likelihood of governmental financial support, such as tax reductions, for parks implementing eco-friendly practices. Parks implementing recycling and energy management are, on average, 3.41 times and 5.3 times more likely to receive these incentives, respectively.

Moreover, recycling activities and air monitoring consistently show a considerable influence on the success of policy and regulation frameworks within the parks. The odds of governmental authorities being involved in park development and operational enhancements are, on average, 4.79 times higher with the implementation of these criteria.

Economic viability is a primary motivation for companies to develop eco-innovation strategies [6]. CHP plants increase the odds of direct economic benefit within the park by 3.89 times (Scenario 1). For example, a CHP plant contributes to the energy savings of roughly 6 million kWh at South Groningen Business Park (Park no 76 from [29]), an eco-cluster

Table 2. Summary of significant predictors influencing the success indicators in eco-innovation parks. Significant independent variables corresponding to each success factor are presented in each cell with the format name (p-value, odds ratio). Area Under the Curve (AUC) measures the reliability of the regression model for each success factor.

Success Factor	**Cooperation with Science and Technology Institutions**	**Organized Coordination**	**Local Diversity of Economic Activities**	**Financial Incentives**	**Clear Designation as an Eco-Innovation Park**	**Location and Regional Infrastructure**	**Policy & Regulation Frameworks**	**Economic Value Added**
Scenario 1	Social and Education (0.0360, 0.3114)	Mobility/Transportation (0.0164, 4.4593) Number of SMEs within parks (0.0356, 1.0009) CHP Plant (0.0383, 0.2948)	Number of SMEs within parks (0.0007, 1.0009)	Recycling (0.0003, 4.5684) Energy Management (0.0347, 6.5081) Mobility/Transportation (0.0347, 0.3050)	Non-Significant Predictors	Number of SMEs within parks (0.0302, 1.0002)	Recycling (0.0023, 4.0863) Air Monitoring (0.0029, 6.1840) Social and Education (0.0626, 3.0369)	CHP Plant (0.0250, 3.8921) Land Use Optimization (0.0255, 0.1800)
AUC	Fair - 0.7043	Fair - 0.7264	Fair - 0.7721	Fair - 0.7548	Poor - 0.6739	Poor - 0.6710	Fair - 0.7751	Fair - 0.7304
Scenario 2	Social and Education (0.0251, 0.3099)	Mobility/Transportation (0.0023, 5.0472)	Air Monitoring (0.0390, 0.1376) Social and Education (0.0426, 0.2332)	Recycling (0.0090, 2.8384) Social and Education (0.0279, 3.1016) Energy Management (0.0441, 4.6933)	Non-Significant Predictors	Water Use Efficiency (0.0061, 0.2649)	Recycling (0.0001, 5.1600) Air Monitoring (0.0201, 4.5308) Number of SMEs country level (0.0496, 5.4445)	Land Use Optimization (0.0130, 0.1772) Mobility/Transportation (0.0288, 0.3437)
AUC	Poor - 0.6831	Fair - 0.7164	Fair - 0.7207	Fair - 0.7399	Poor - 0.6836	Poor - 0.6611	Fair - 0.7792	Poor - 0.6936
Scenario 3	Social and Education (0.0264, 0.3122)	Mobility/Transportation (0.0027, 4.9202)	Air Monitoring (0.0038, 0.1312) Social and Education (0.0447, 0.2364)	Recycling (0.0096, 2.8185) Social and Education (0.0321, 3.0290) Energy Management (0.0451, 4.6885)	Non-Significant Predictors	Water Use Efficiency (0.0059, 0.2636)	Recycling (0.0002, 5.1116) Value Added by SMEs (0.0193, 7.3108) Air Monitoring (0.0245, 4.3091)	Land Use Optimization (0.0129, 0.1769) Mobility/Transportation (0.0296, 0.3448)
AUC	Poor - 0.6821	Fair - 0.7103	Fair - 0.7110	Fair - 0.7386	Poor - 0.6813	Poor - 0.6659	Fair - 0.7961	Poor - 0.6963

of four companies using by-products and energy flow exchange. This result aligns with a study by [35], which highlights that CHP plants play a crucial role in enhancing the economic value of eco-parks by improving operational efficiency and minimizing carbon emission costs.

Regarding the first scenario, the results suggest that the number of SMEs within innovation parks has a slight but measurable impact on organized coordination, local economic activity diversity, and regional infrastructure. Each additional SME within a park marginally increases the likelihood of these success factors. In the second scenario, the odds ratio of 5.4445 for the number of SMEs at the national level indicates that the probability of policy and regulatory framework success factors occurring in the park is 5.44 times higher when comparing the highest and lowest values of SMEs in a country. Similarly, as the economic value contribution of SMEs increases, the odds of this success factor occurring rise approximately 7.31 times when comparing the highest and lowest values of SME contributions. This suggests that a high concentration of SMEs and their significant economic contributions at the national level drive policy actions that enhance eco-innovation development.

The impact of criteria on different success indicators can vary based on the odds ratio, which could reflect either a positive or negative influence. Furthermore, it is essential to consider that eco-innovation parks in the dataset implement a range of eco-activities, rather than focusing on single-innovation aspects. Consequently, prediction profilers serve as a powerful tool to identify which combinations of eco and sub-eco initiatives lead to an optimal likelihood of success due to interaction effects. The importance of a predictor can be assessed by its steepness. By changing factors with a positive slope while keeping others constant, it is possible to examine which combination of initiatives optimizes the likelihood of success. For example, data from Table 3 suggests that promoting Mobility/Transportation and Energy Efficient Building while keeping the rest constant increases the probability of achieving the success factor of organized coordination to 97.3%.

Table 3. Prediction profilers: Combinations of eco-initiatives and predicted optimized outcomes.

Success Factor	**Eco Initiatives Combination**	**Outcome(%)**
Cooperation with Science and Technology Institutions	Air Monitoring, Mobility/Transportation	86.4
Organized Coordination	Mobility/Transportation, Energy Efficient Building	97.3
Local Diversity of Economic Activities	Land Use Optimization, Water Use Efficiency, Recycling, Mobility/Transportation	84.9
Financial Incentives	Air Monitoring, Social & Education, Energy Efficient Building, Land Use Optimization, Energy Management, Recycling	99.6
Clear Designation as an Eco-Innovation Park	Social & Education, Energy Efficient Building, Air Monitoring	77.4
Location and Regional Infrastructure	Land Use Optimization, Energy Management, Mobility/Transportation	78.8
Policy and Regulation Frameworks	Air Monitoring, Social & Education, Energy Management, Recycling	95.5
Economic Value Added	CHP plant, Energy Efficient Building, Recycling, Water Use Efficiency	96.5

5.2 On answering sub RQ 2 - Characteristics of efficient and inefficient regions

The results of the DEA BCC model indicate that 25 out of 72 eco-innovation parks were deemed efficient, encompassing various types: public, private, and public-private partnerships. It was observed that efficient parks operate in smaller areas but create approximately 8.42 times more job opportunities than inefficient ones (Figure 3). The projection of inefficient parks onto the efficient frontier also highlights areas for improvement to reach efficiency. For example, the performance of San Daniele s.c.a.r.l Agrifood park, which was evaluated in combination with its peers—Mipo & Onsan (Ulsan EIP Project), Parque Tecnológico Galicia Tecnópole, and Eco-Town Kawasaki parks—with weighted values of 0.0412, 0.5172, and 0.4416 respectively, implies that to become efficient, San Daniele s.c.a.r.l Agrifood Park should aim to mimic the characteristics of Parque Tecnológico Galicia Tecnópole at 51.72%, followed by Eco-Town Kawasaki at 44.16%, and so on.

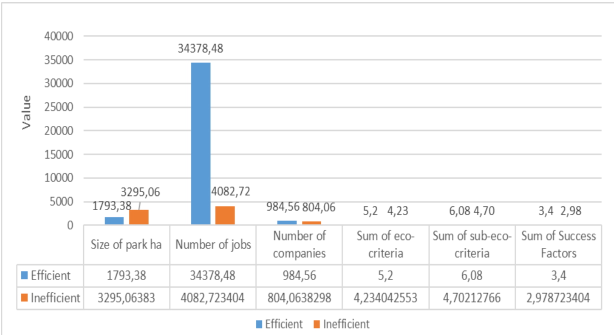

Fig. 3. Average performance of efficient and inefficient regions based on mean descriptive statistics of input and output factors.

Figure 4 demonstrates that efficient region is more prominent in the occurrence of organized coordination, financial incentives, location and regional infrastructure, policy and regulation frameworks, and direct economic benefits compared to inefficient ones. The most significant disparities are observed in organized coordination, financial incentives, and location and regional infrastructure. On the other hand, inefficient regions exhibits a higher presence of clear designation as eco-innovation parks. This designation enhances the image and credibility of the parks, improving marketing and communication standards. This could be due to a compensatory mechanism, where the designation as eco-innovation parks helps rebrand and attract new business partners and investors. However, interpretations of this are varied.

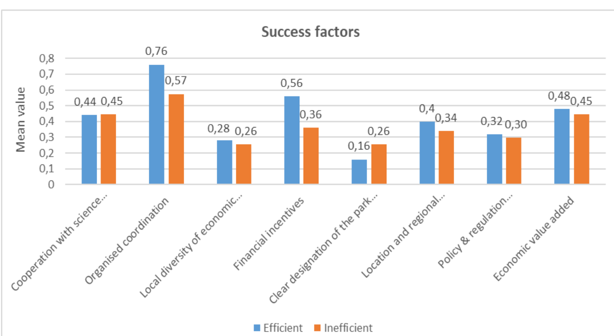

Fig. 4. Average occurrence of success factors in efficient and inefficient regions based on mean descriptive statistics.

With regard to the implementation of eco-criteria within the parks (Figure 5), efficient regions on average show higher levels of air pollution prevention, biodiversity, cultural/social/health initiatives, energy efficiency, land use optimization, material flows, and renewable energy initiatives. The differences are particularly notable in the implementation of cultural/social/health initiatives, energy efficiency, biodiversity, and renewable energy initiatives. In contrast, inefficient regions perform slightly better in waste management and water management. This counterintuitive result requires further investigation into the nature of the industrial activities and park setups, as each park operates with its own distinct objectives. For example, chemical parks in the dataset show more successful experiences in waste management. It should also be noted that waste management is the most commonly implemented eco-criterion, present in 120 out of 168 parks, making it difficult to differentiate performance based solely on this criterion.

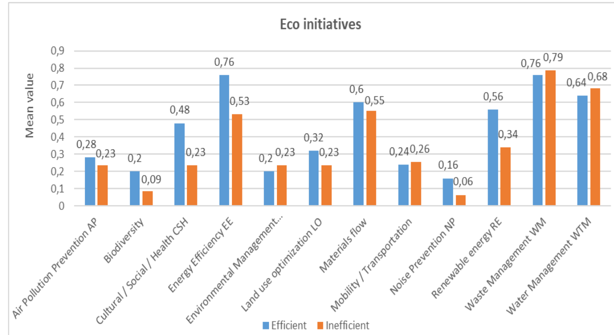

Fig. 5. Average eco-initiatives adoption in efficient and inefficient regions based on mean descriptive statistics.

5.3 On answering sub RQ 3 - Efficiency practices and policy suggestions

Analyzing the DEA result, it was found that Eco-Town Kawasaki in Japan, Parque Tecnológico Galicia Tecnópole in Spain, BASF Verbund site Ludwigshafen and Pharma- und Chemiepark Wuppertal in Germany, and Mipo & Onsan (Ulsan EIP Project) in South Korea are the top five parks used as references for inefficient ones. Investigating the detailed descriptions of these parks from the survey [29], several common characteristics among them are identified.

The first characteristic is the application of the Eco-Management and Audit Scheme (EMAS) and certified environmental standards at the park scale. Environmental management certifications, such as ISO 14001 and EMAS, although not inherently linked to the deployment of novel technologies or the creation of intricate integrated systems, necessitate proactive measures in various facets of environmental performance within industrial parks [29]. An example is the Parque Tecnológico Galicia Tecnópole park in Spain (Park no 90 from [29]), which stands as a pioneer in obtaining these certifications among European business parks.

Secondly, government involvement and facilitation are crucial for park development and operation. The involvement of many stakeholders, including researchers and an efficient coordination unit, is essential for success. The Mipo & Onsan (Ulsan EIP Project) experiences the highest number of success factors among all the parks. This government-operated eco-industrial park in South Korea adopts a comprehensive strategy across three policy levels: national, municipal, and local. The findings suggest that the complexities of resource exchange networks require efficient organizational and institutional setups. These agents act as coordinators to bridge gaps in inter-firm collaboration, enhance communication, and ensure the needs of relevant stakeholders are met. Moreover, the analysis of efficient parks in the dataset indicates that government policy plays a key role in providing political, coordinative, educational, and financial support. It is also necessary to have a standardized and comprehensive framework for assessing the success of the parks.

Furthermore, financial incentives are instrumental in diminishing economic barriers and promoting the planning and implementation of eco-innovation activities within industrial parks, particularly for SMEs. Regarding the primary barriers encountered by SMEs mentioned in [42], coordination unit should create an environment where SMEs can overcome financial and resource constraints, fostering more equity within the alliance through cluster performance development. Regulation should be flexible, encouraging mutual trust and the involvement of relevant stakeholders in the parks, including local economic players and research institutes. This encourages continual updates and improvements. The government should not only provide financial and institutional support, and monitoring and mediation but also facilitate stakeholder participation via bottom-up activities to build successful regional development [33].

Thirdly, these efficient parks benefit from good geographical locations and proximity to transportation infrastructure. Findings by [54] show that proximity to cities is a critical factor for the establishment of new industrial parks, due to the significance of city infrastructure and accessibility in the sustainable planning of these parks.

By examining the top five referenced efficient parks, the findings reveal common characteristics contributing to their success. To become more efficient, inefficient regions are suggested to implement standardized environmental management at a park scale and establish efficient organizational setups. Policymakers could facilitate coordination among relevant economic actors and provide financial support to enhance regional transitions to a circular economy. Furthermore, a suitable location that ensures accessibility to infrastructure and transportation, close proximity to markets, and utilities is crucial, as highlighted in [41] when deciding on the location of industrial parks to help them benefit from socioeconomic and environmental sustainability values.

6 CONCLUSION

In this research, we aimed to investigate the influence of sustainability initiatives and the presence of SMEs on the effectiveness of Eco-Innovation Parks (EIPs), inspired by the confluence of sustainability and circular economy concepts. The study also sought to understand common patterns or practices among efficient regions that could inspire improvements in less efficient areas. Quantitative analysis methods, including binary logistic regression and Data Envelopment Analysis (DEA), were employed.

The research found that while initiatives such as social and educational programs, mobility and transportation, recycling, and energy management significantly influence the occurrence of success factors within EIPs, it is more effective to assess a combination of eco-criteria as a strategy to optimize success rather than focusing on individual initiatives. Efficient parks in general adopt a higher number of eco-criteria, resulting in significantly better outcomes in organized coordination, financial incentives, and policy and regulation frameworks. Additionally, the presence of SMEs within the parks and their economic contributions at the national level positively impact policy and regulatory success factors.

The counter-intuitive results observed in some areas were not interpreted due to the scope and methodology used in this research. This highlights the complexities in assessing the efficiency of EIPs, suggesting that future research should consider the distinct characteristics and objectives of individual parks. Additionally, by examining the patterns of efficient regions, the research emphasizes the importance of standardized environmental management processes, government involvement, efficient inter-firm collaboration, and the strategic location of parks. The findings indicate that government policy could play an enabling role, indicating that legislation is necessary to facilitate park development, help SMEs overcome barriers, and provide a standardized assessment framework. The combination of top-down and bottom-up policies is important for achieving these goals.

6.1 Limitations

The research faced several limitations, mainly due to the scarcity of data on the performance of SMEs within the parks and the small size of the dataset. Because of that, the study had to rely on certain assumptions, making it difficult to accurately evaluate the actual role and contribution of SMEs within the parks. The small dataset also restricts the number of predictors that can be examined in the impact analysis to ensure the model's validity, while all eco-innovation parks in the dataset implement multiple eco-activities rather than focusing on single-innovation aspects.

One approach that could be helpful is using an interactive profiler to identify which combination of eco and sub-eco initiatives leads to the optimal chance of success. Furthermore, due to the binary nature of many attributes, it is challenging to evaluate the level of efficiency based solely on the presence or absence of eco-initiatives and success factors as the absence of eco or sub-eco criteria could also result from missing data or a lack of relevant information at the time of the study, rather than the parks not implementing these activities. Therefore, the results need to be interpreted with caution.

6.2 Future research

Future research should explore the operation and performance of SMEs within the parks using larger and more diverse datasets. Additionally, it is important to note that the regression analysis does not imply causality, hence, leaving some counterintuitive results open for further explanation. Future studies could delve deeper into how certain combinations of initiatives affect the efficiency of EIPs and to what extent, regarding specific national and local contexts. Furthermore, future research should aim to collect more detailed data on the operation of SMEs within EIPs to better understand their specific roles and contributions to the resource exchange networks. Additionally, while DEA is a robust method for efficiency analysis, it should be hybridized with other approaches such as Multiple-Criteria Decision-Making (MCDM) methods, soft computing techniques, or machine learning to enhance its efficiency and increase discriminatory power—an area where DEA often faces limitations. For instance, MCDM methods such as TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and SAW (Simple Additive Weighting) provide simple and clear rankings of clusters based on weighted criteria, aiding decision-makers in selecting the best options according to their priorities and the problem context. On the contrary, soft computing techniques and machine learning can handle complex, non-linear relationships and offer predictive capability.

This research adds to existing theory of meso-level analysis of cluster performance by providing a methodological approach that combines binary logistic regression and Data Envelopment Analysis (DEA), creating a robust framework for assessing the efficiency and sustainability of industrial parks. The insights from the findings could serve as a reference for policymakers to standardize assessment frameworks and support the development of EIPs through social, educational, and infrastructural interventions.

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