Journal of Operations Intelligence, Volume 3, Issue 1 (2025) 308-323

SCIENTIFIC OASIS

Journal of Operations Intelligence

Journal homepage: www.jopi-journal.org
eISSN: 3009-4267

A Data Evolvement Analysis for Sustainable Performance Evaluation of Educational Resource Use in Architecture Universities

Youzhi Pan[1], Min Kong[1], Weijian Zhang[1] and Amir M. Fathollahi-Fard[2,*]

[1] School of Economics and Management, Anhui Normal University, Wuhu, 241003, China
[2] Département d'Analytique, Opérations et Technologies de l'Information, Université de Québec à Montreal, 315, Sainte-Catherine Street East, H2X 3X2, Montreal, Canada

ARTICLE INFO

Article history:
Received 11 February 2025
Received in revised form 27 April 2025
Accepted 22 May 2025
Available online 27 May 2025

Keywords:
Architecture Universities; Data Envelopment Analysis; Sustainable Development; Scale Efficiency.

ABSTRACT

In the context of China's dual-carbon strategy and the ongoing promotion of green campus initiatives, efficient resource allocation in universities, particularly architecture-focused institutions, has garnered growing attention. This study evaluates 28 architecture universities in mainland China using Data Envelopment Analysis (DEA), applying standardized input–output indicators. The analysis examines three key dimensions: technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE). The results indicate that while many universities exhibit strong managerial efficiency, significant disparities in scale efficiency persist, suggesting widespread misalignments between institutional size and resource utilization. Further classification based on returns to scale (RTS) reveals distinct inefficiency types, providing a foundation for targeted improvement strategies. The study concludes with policy recommendations aimed at differentiated resource optimization and sustainable campus development, offering practical insights to enhance the green performance and long-term sustainability of architecture universities.

1. Introduction

Against the backdrop of the "dual-carbon" strategy and the growing emphasis on sustainable development, universities, as resource-intensive public building units, are increasingly becoming vital platforms for green transformation. Green Campus construction encompasses not only energy-efficient architecture, the use of environmentally friendly materials, and spatial optimization, but also the promotion of green education and the cultivation of ecological consciousness [1-3]. The energy consumption and carbon emissions throughout the life cycle of educational buildings are considered key indicators for assessing green performance. Existing studies have evaluated the

---

[*] *Corresponding author.*
E-mail address: fathollahifard.amirmohammad@courrier.uqam.ca

https://doi.org/10.31181/jopi31202549

energy-saving potential of such buildings through carbon factor calculations and building energy efficiency analyses [4, 5].

In recent years, the Green Campus concept has evolved from a focus on physical space construction to the integration of behavioral and cognitive dimensions, emphasizing the synergy between “soft environments” and “hard resources.” Research has shown that green building environments can shape students’ environmental awareness and stimulate participatory behavior, thereby fostering a “green learning–living community” [6-9]. Moreover, architecture universities play a dual role in campus space renewal by incorporating green principles into curriculum design, architectural projects, and practice platforms—serving as both the builders of Green Campuses and the promoters of green education [10, 11]. The performance evaluation of Green Campuses has also expanded from a traditional focus on physical indicators such as energy and water usage to include the efficiency of educational space allocation, campus operational intelligence, and student behavioral engagement [12-14]. This shift not only reflects a deepening of the Green Campus concept but also provides a new analytical framework for examining the input–output efficiency of educational resource utilization in architecture universities.

As the Green Campus concept continues to deepen, architecture universities are increasingly confronted with both challenges and opportunities in reshaping their educational responsibilities. As theoretical advocates and practical drivers of green building, ecological design, and urban sustainability, architectural education not only fulfills the fundamental mission of talent cultivation but also bears the responsibility of disseminating green principles and responding to global sustainable development strategies [15, 16]. Architectural education inherently relies on practical platforms, instructional spaces, and design resources, and its pedagogical models and curricular structures are directly linked to how educational resources are structured and utilized efficiently. In recent years, scholars have pointed out that the curriculum and training programs of architectural education should more closely align with sustainability goals, promoting the integration of green design and ecological planning into both classroom instruction and design studio work [17]. This shift reflects not only a response to evolving industry demands but also a restructuring of the internal architecture of higher education itself. The ongoing reform toward employment-oriented education has further pushed architecture universities to emphasize the development of students’ comprehensive abilities and social adaptability, thereby fostering a more dynamic alignment between academic programs and labor market needs [18].

However, in practice, the relationship between educational resource allocation, the utilization of teaching facilities, and graduate outcomes in architecture universities remains underexplored and insufficiently quantified. This structural gap has led to discrepancies in output performance across institutions, even under high investment conditions, rendering it difficult to effectively measure resource use efficiency or provide evidence-based recommendations for policy and institutional improvement.

To enable scientific and objective evaluation of educational resource performance, an increasing number of scholars have introduced Data Envelopment Analysis (DEA) as a quantitative tool to assess resource utilization efficiency in higher education. DEA is a non-parametric efficiency evaluation method that allows the comparison of relative efficiencies among multiple decision-making units under multiple input and output conditions. It has been widely applied in performance evaluation across various public sectors, including education, healthcare, and energy management [19, 20].In the field of education, DEA has been employed to evaluate universities’ teaching efficiency, research performance, and knowledge transfer capabilities. It is particularly well-suited for comparing student training outcomes, research output, and social impact under diverse input conditions such as faculty size, space allocation, and financial resources [21, 22]. Moreover, the DEA model exhibits strong flexibility and explanatory power, with extensions such as network DEA, two-stage DEA, and super-efficiency DEA, allowing it to adapt to the complexity of educational systems [23].

Despite its widespread application in education performance analysis, few studies have focused specifically on architecture universities, especially from the perspective of green education. There remains a gap in the literature concerning the integration of educational resource allocation and graduate employment performance into a unified efficiency evaluation framework. On the one hand, the particularities of resource distribution in architecture education have not been sufficiently incorporated into mainstream DEA models; on the other hand, graduate employment outcomes—an essential reflection of educational effectiveness—are still underrepresented in efficiency metrics. By combining the Green Campus perspective with the unique characteristics of architecture education, constructing a DEA model that centers on employment performance can help identify both strengths and inefficiencies in resource use, thus providing empirical support for educational administrators and policymakers. To better understand the existing research landscape and highlight the relevance of this study, the literature was categorized based on three core thematic areas: educational efficiency, green campus performance, and architectural education reform. The detailed data and results can be seen in Table 1.

Table 1
Literature overview based on research focus categories

Research Focus Category	Representative Literature	Brief Description
Educational Resource Efficiency	Almeida et al., [22]; Liu & Tsai, [24]; Sun et al., [25]; Xiong et al., [26].	DEA-based analyses on higher education efficiency and resource allocation using multi-input-output models.
Green Campus & Building Performance	Laporte & Cansino, [27]; Zhao et al., [28]; Shuqin et al., [29]; Baricco et al., [30]; Li et al., [3]; Zhu & Liu, [31]; Chen & Xia, [32]; Guo et al., [33]; Zou et al., [34].	Studies on campus-level environmental performance, energy strategies, and low-carbon or green infrastructure planning.
Architectural Education & Curriculum	Mohamed & Ibrahim, [19]; Zhu & Liu, [31].	Research focusing on sustainability integration in architectural curricula and pedagogy reform in design education.

In response, this study adopts the DEA methodology to evaluate the efficiency of 28 architecture universities in China. Representative input variables such as the number of faculty, instructional space, and student enrollment are selected, along with key output indicators including employment rate, postgraduate enrollment rate, and the proportion of graduates employed in the architecture industry. Based on these variables, an evaluation system is established to assess the input–output efficiency of educational resource use and employment outcomes. By comparing relative efficiencies across institutions and analyzing their returns to scale, the study identifies resource redundancies and structural imbalances and proposes optimization strategies.

The structure of this paper is as follows: Section 2 introduces the research methodology, including the DEA model, variable selection, and data sources. Section 3 presents the empirical analysis, including the efficiency evaluation results and return-to-scale classification, along with a comparative discussion. Section 4 offers managerial implications and policy recommendations based on the findings. Finally, Section 5 concludes the study and outlines its limitations and directions for future research.

2. Methodology

This chapter introduces the methodological framework adopted in this study. It begins by explaining the theoretical foundation and applicability of Data Envelopment Analysis (DEA) as a performance evaluation tool, followed by the mathematical structure of DEA models and the specific model types employed in this research. Lastly, it describes the process of variable selection and data collection.

2.1. Research Method Overview

Data Envelopment Analysis (DEA) is a non-parametric method based on linear programming, first proposed by Charnes, Cooper, and Rhodes in 1978. It is designed to evaluate the relative efficiency of a set of Decision-Making Units (DMUs) under multiple input and output conditions. Unlike traditional regression-based approaches, DEA does not require a predefined functional form or manually assigned weights for input and output variables. As such, it has been widely applied in public management fields such as education, healthcare, and finance. The core idea of DEA is to construct an empirical "efficiency frontier" based on the most efficient units in the sample, and to measure the distance of other units from this frontier to determine their relative efficiency. Efficiency scores range from 0 to 1, where a score of 1 indicates that the DMU is relatively efficient within the sample, and a score less than 1 denotes inefficiency.

Two commonly used DEA models are the CCR model (Charnes-Cooper-Rhodes) and the BCC model (Banker-Charnes-Cooper). The CCR model assumes constant returns to scale (CRS) and is suitable for scenarios where DMUs operate at similar scales. It measures overall technical efficiency (TE). In contrast, the BCC model introduces the assumption of variable returns to scale (VRS), allowing for the decomposition of efficiency into pure technical efficiency (PTE) and scale efficiency (SE). To comprehensively evaluate the efficiency of resource allocation in architecture universities, this study applies both the CCR and BCC models. The CCR model is first used to calculate the overall technical efficiency of each university, followed by the BCC model to separate managerial performance (PTE) from scale effects (SE). This dual-model approach enables us to identify whether inefficiencies stem primarily from suboptimal management or from inappropriate institutional scale.

2.2. Model Structure Description

Assume there are nnn decision-making units (DMUs), each utilizing m input variables to produce sss output variables. Let the DMU under evaluation be denoted as DMU_O, with inputs represented by x_{io} and outputs by y_{ro}. The goal of the DEA model is to identify a set of weights $\lambda_j\ (j=1,2,...,n)$, such that a hypothetical composite unit–constructed as a linear combination of peer DMU_S–can achieve outputs at least as great as DMU_O, using no more than a proportionally reduced amount of inputs. The technical efficiency calculation model is derived as follows.

(1) Fractional Programming Form

$$Max\frac{\sum_{r=1}^{s}u_r y_{ro}}{\sum_{i=1}^{m}v_i x_{io}} \tag{1}$$

The original CCR model is a fractional programming problem that seeks to determine a set of optimal weights for inputs and outputs to maximize the efficiency score of the evaluated unit:

s.t.:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad \text{j=1,...,n} \qquad (2)$$

$$\text{u}_r \ge 0, \quad \text{v}_i \ge 0$$

Where:

y_{rj} and x_{ij} denote the $r-th$ output and $i-th$ input of DMU j ; u_r, v_i are the output and input weights to be determined. As a nonlinear model, it cannot be directly solved by standard linear programming techniques. Therefore, a transformation is required.

(2) Charnes-Cooper Transformation

$$t = \frac{1}{\sum_{i=1}^{m} v_i x_{io}}, \quad \mu_r = t u_r, \quad \omega_i = t v_i \qquad (3)$$

To linearize the fractional objective function, the Charnes-Cooper transformation is applied by defining:

Substituting into the original model, we obtain the equivalent linear programming form:

$$Max \sum_{r=1}^{s} u_r y_{ro} \qquad (4)$$

Subject to:

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} \omega_i x_{ij} \le 0, \quad \text{j=1,...,n}$$
$$\sum_{i=1}^{m} \omega_i x_{io} = 1, \quad u_r \ge 0, \quad \omega_i \ge 0 \qquad (5)$$

(3) Dual Model: Input-Oriented CCR Formulation

The above model can be transformed into its dual form, which corresponds to the input-oriented CCR model. The dual linear programming formulation is:

$$\text{Min } \theta$$
$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io}, & i = 1, \ldots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}, & r = 1, \ldots, s \\ \lambda_j \ge 0, & j = 1, \ldots, n \end{cases} \qquad (6)$$

Where θ denotes the relative efficiency score of DMU_O (i.e., Technical Efficiency, TE), where $0<\theta \le 1$; λ_j represents the weighting coefficient assigned to peer DMU_S , used to construct the linear combination as a comparison benchmark. If $\theta = 1$ and all constraints are satisfied, DMU_O is considered efficient within the current sample; otherwise, it is deemed inefficient. The CCR model projects all DMUs onto an efficiency frontier with a linear boundary, implicitly assuming that all DMUs operate under constant returns to scale.

Add a scale constraint based on the above: $\sum_{j=1}^{n} \lambda_j = 1$ .The BCC model is obtained as follows:

$$\text{Min} \quad \theta$$
$$\text{s.t.}\begin{cases} \sum_{j=1}^{n}\lambda_j x_{ij} \le \theta x_{io}, & i=1,\dots,m \\ \sum_{j=1}^{n}\lambda_j y_{rj} \ge y_{ro}, & r=1,\dots,s \\ \sum_{j=1}^{n}\lambda_j = 1, & j=1,\dots,n \\ \lambda_j \ge 0, & j=1,\dots,n \end{cases} \tag{7}$$

This constraint changes the efficiency frontier from a straight line to a "convex hull", allowing the model to capture differences in production efficiency at different scales and avoid the phenomenon of high-scale DMU "monopolizing" efficiency evaluation.

The scale efficiency of each university can be derived by comparing the results of the two models: $SE = \frac{TE(CCR)}{PTE(BCC)}$. In addition, the returns to scale (RTS) of each DMU can be determined based on its projection position on the efficiency frontier. This allows classification into increasing returns to scale (IRS), decreasing returns to scale (DRS), or constant returns to scale (CRS), thereby providing strategic suggestions for scale adjustment in universities. This study adopts an input-oriented DEA model, as educational administrators are typically more concerned with optimizing resource inputs without compromising output levels. Such a focus aligns with the practical goals of higher education institutions to control costs and enhance operational efficiency.

To evaluate the efficiency of educational resource allocation and employment outcomes in architecture universities under the background of Green Campus development, this study selects input and output variables based on the practical considerations of university teaching and administrative management. The indicators are shown in Table 2.

Table 2
Input and Output Variables Used in the DEA Model

Category	Variable	Description
Inputs	Number of Architecture Faculty Members	Measures human resource investment in teaching and research
	Instructional Space (sqm)	Represents physical infrastructure supporting educational activities
	Number of Enrolled Architecture Students	Reflects institutional size and scale of student intake
Outputs	Graduate Employment Rate	Indicates the proportion of graduates successfully employed
	Postgraduate Enrollment Rate	Reflects students' academic progression and institutional academic reputation
	Employment Proportion in Architecture Sector	Assesses the alignment between education and architecture industry demands

2.3. Data Sources and Processing

This study selects 28 architecture universities in mainland China as the decision-making units (DMUs). Data were primarily obtained from publicly available sources, including official university websites, annual graduate employment quality reports, and the Ministry of Education’s National Higher Education Basic Data Statistics System. The most recent available year was used for all data to ensure comparability and completeness of the cross-sectional dataset. In order to more clearly understand the geographical representativeness and institutional diversity of the sample, the spatial distribution of the 28 universities selected in this article is shown in Figure 1. This distribution not only reflects the regional concentration of architectural education, but also highlights the different local development contexts that may affect institutional efficiency and resource allocation patterns. The darker shades represent provinces with a higher concentration of institutions. Notably, Jiangsu, Hunan, Guangdong, and Shaanxi provinces have relatively more architecture-focused universities, indicating regional clustering of architectural education resources. In contrast, large areas in the western and northeastern regions show limited presence, suggesting potential disparities in spatial distribution and access to architectural education.

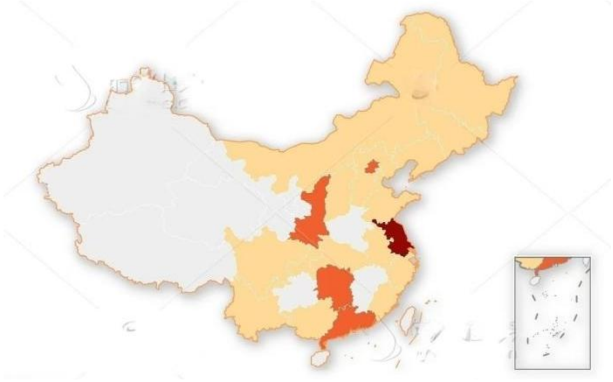
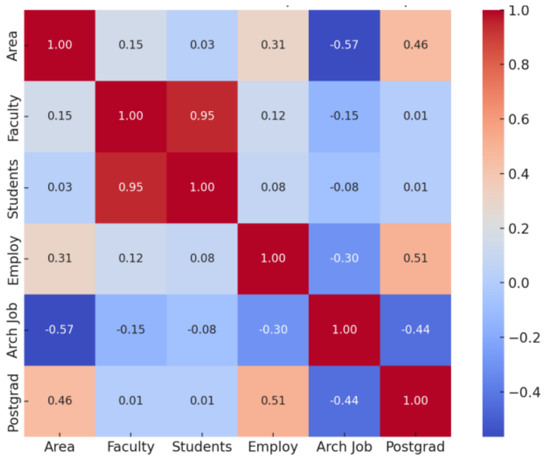


Fig. 1. Geographical Distribution of 28 Architecture Universities.



	Area	Faculty	Students	Employ	Arch Job	Postgrad
Area	1.00	0.15	0.03	0.31	-0.57	0.46
Faculty	0.15	1.00	0.95	0.12	-0.15	0.01
Students	0.03	0.95	1.00	0.08	-0.08	0.01
Employ	0.31	0.12	0.08	1.00	-0.30	0.51
Arch Job	-0.57	-0.15	-0.08	-0.30	1.00	-0.44
Postgrad	0.46	0.01	0.01	0.51	-0.44	1.00

Fig. 2. Correlation Matrix of DEA Inputs and Outputs.

To ensure that the selected input and output variables are conceptually valid and statistically suitable for the DEA model, we conducted a correlation analysis. This helps to assess whether the variables are independent enough to avoid redundancy while still capturing different aspects of university performance. The results are visualized in the form of a correlation matrix as shown in Figure 2. The result illustrates the Pearson correlation matrix among the selected input and output variables. The inputs–faculty size, teaching space, and student population–are moderately correlated, especially between faculty and students, indicating alignment between scale and staffing. Among outputs, the employment rate and architecture-related employment proportion show a positive association, while the postgraduate rate is negatively correlated with both, suggesting a trade-off between further education and immediate employment outcomes. The relatively low correlations between inputs and outputs confirm that each indicator captures distinct dimensions of performance, justifying the use of a multi-input, multi-output DEA model for efficiency evaluation.

To eliminate the influence of differences in units and magnitudes among variables (Table A1), all data were normalized prior to modeling using the min-max scaling method, which maps each indicator into the [0,1] range. The normalization was conducted according to the following formula:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{8}$$

where x is the original value, and x' is the normalized value. The standardized data are shown in Table 3.

Table 3
Standardization of input-output indicators of the School of Architecture

Name of college	Teaching Area (10k m²)	Faculty (People)	Students (People)	Employment Rate (%)	Architecture Job (%)	Postgraduate Rate (%)
Tsinghua Univ.	0.430	0.192	0.161	0.985	0.115	0.642
Tongji Univ.	0.399	0.364	0.309	0.942	0.126	0.398
Southeast Univ.	0.172	0.243	0.215	0.911	0.147	0.916
Tianjin Univ.	0.889	0.214	0.210	0.830	0.224	1.000
SCUT	0.637	0.180	0.207	1.000	0.129	0.445
Chongqing Univ.	0.348	1.000	1.000	0.745	0.279	0.472
HIT	0.546	0.259	0.232	0.937	0.183	0.544
SWJTU	0.164	0.176	0.169	0.916	0.398	0.740
Central South Univ.	0.598	0.203	0.226	0.870	0.173	0.578
Wuhan Univ.	0.482	0.182	0.123	0.695	0.154	0.598
Zhejiang Univ.	1.000	0.439	0.233	0.772	0.100	0.533
BUCEA	0.107	0.199	0.220	0.908	0.634	0.363
SDAU	0.153	0.207	0.184	0.901	0.647	0.444
AHJZU	0.222	0.137	0.129	0.667	0.464	0.356
Fuzhou Univ.	0.371	0.100	0.109	0.361	0.192	0.584
Chang'an Univ.	0.260	0.226	0.298	0.709	0.546	0.537
Hunan Univ.	0.291	0.169	0.136	0.703	0.175	0.396
HEBUT	0.190	0.188	0.203	0.594	0.380	0.492
Nanjing Tech	0.578	0.165	0.169	0.649	0.382	0.573
KMUST	0.283	0.248	0.238	0.224	0.379	0.279
Shenzhen Univ.	0.436	0.226	0.121	0.837	0.123	0.565
Suzhou Univ. Sci. & Tech	0.132	0.190	0.169	0.792	0.245	0.316
TYUT	0.367	0.331	0.295	0.594	0.198	0.481
SJZU	0.114	0.203	0.175	0.427	0.868	0.405
Jilin Jianzhu Univ.	0.100	0.135	0.100	0.298	1.000	0.100
IMUT	0.212	0.152	0.120	0.100	0.188	0.221
Guangxi Univ.	0.289	0.308	0.397	0.384	0.167	0.486
XAUAT	0.196	0.360	0.354	0.609	0.559	0.360

3. Empirical Analysis

This chapter conducts an empirical analysis of 28 architecture universities based on the DEA models established in Chapter 2, aiming to comprehensively evaluate their efficiency in educational resource allocation and graduate employment performance within the context of Green Campus development. The analysis covers model computation and data overview, efficiency score results, scale efficiency and returns to scale classification, as well as institutional categorization and targeted optimization recommendations.

3.1. Efficiency score results analysis

Based on standardized cross-sectional data, this study applies two DEA models─CCR (Constant Returns to Scale) and BCC (Variable Returns to Scale)─to evaluate the input‑output efficiency of 28 architecture universities in China. An input-oriented model is employed to examine whether resource redundancy exists under the condition of maintaining the same output level.

The calculations are implemented using Python, and the following efficiency indicators are obtained. Technical Efficiency (TE): Derived from the CCR model, it reflects the overall efficiency of resource utilization. Pure Technical Efficiency (PTE): Obtained from the BCC model, it isolates the effect of scale and focuses on management and allocation efficiency. Scale Efficiency (SE): Calculated as the ratio of TE to PTE, indicating whether the institution operates at an optimal scale. Returns to Scale (RTS): Identifies whether a university is experiencing increasing, constant, or decreasing returns to scale at its current operational level. The results are presented in Table 4 and Figure 3.

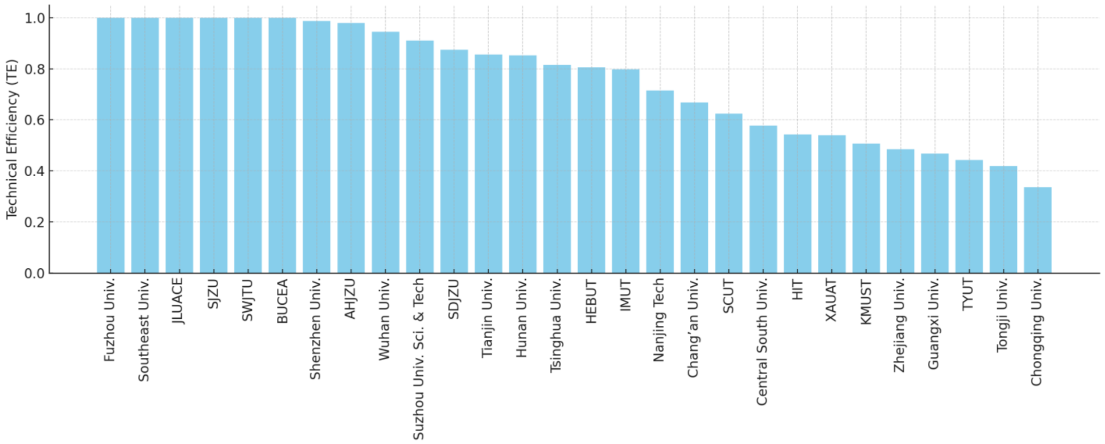


Fig. 3. Comprehensive Technical Efficiency (CCR Model) of Architecture Universities

According to the efficiency decomposition results, 6 out of 28 architecture universities achieved a technical efficiency (TE) score of 1 under the CCR model, indicating that these institutions have reached optimal performance in terms of both resource allocation and operational scale. Meanwhile, more than half of the universities recorded a pure technical efficiency (PTE) score of 1 under the BCC model, suggesting that they exhibit strong management and organizational efficiency, although their overall efficiency is constrained by scale-related factors.By comparing TE and PTE, the scale efficiency (SE) of each university can be derived, revealing the underlying causes of efficiency losses. Some universities, despite achieving PTE = 1, still fall short of full efficiency due to suboptimal institutional scale (SE < 1). For instance, Chongqing University reported a TE of only 0.336, which indicates a significant mismatch between its resource inputs and educational outputs, placing it among the least efficient institutions. A further look at its PTE and SE scores suggests that the inefficiency mainly stems from an inappropriate scale structure rather than poor management practices.

Moreover, the efficiency decomposition results provide information on returns to scale (RTS). The analysis shows that a number of universities operate under increasing returns to scale (IRS), implying that modest expansion could improve their efficiency. Conversely, some institutions exhibit decreasing returns to scale (DRS), suggesting that their current scale may be excessive, leading to resource waste or growing management challenges.

In summary, the overall high level of pure technical efficiency combined with significant variation in total efficiency highlights the generally sound management capabilities of architecture universities, while also pointing to considerable room for improvement in scale optimization. The next section will analyze the scale efficiency results in detail and explain and compare them in light of the actual performance of each university.

3.2. Scale efficiency analysis

Within the framework of the DEA methodology, scale efficiency (SE) is used to assess whether a decision-making unit operates at an optimal scale, given its existing management capability. The DEA evaluation of 28 architecture universities reveals that their scale efficiency values are generally high, indicating overall good performance, though a certain degree of structural differentiation still exists. The results are shown in Figure 4.

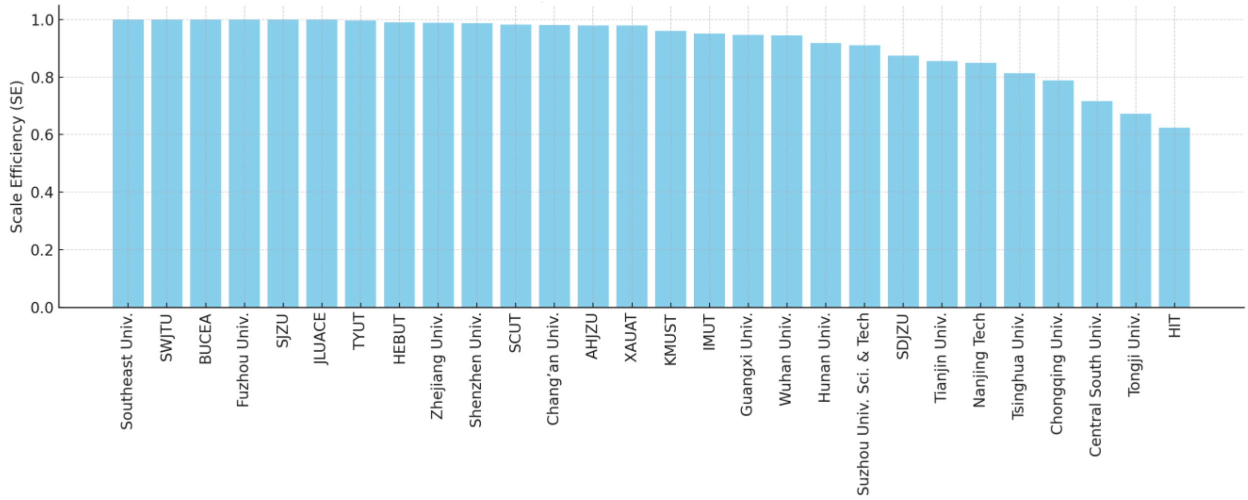


Fig. 4. Scale Efficiency (SE) of 28 Architecture Universities

According to the results, six universities achieved a scale efficiency (SE) score of 1, indicating that their current operational scale is well-aligned with resource allocation, without significant inefficiencies or underutilization. These institutions, such as Fuzhou University, Southeast University, and Southwest Jiaotong University, have demonstrated a dynamic balance between resource structure and institutional scale. However, several universities exhibit scale efficiency scores significantly below the sample average. For instance, both Tongji University and South China University of Technology recorded SE values below 0.7, with the latter at only 0.624—the lowest among all sampled institutions. This suggests a substantial marginal mismatch between resource inputs and educational outputs, potentially caused by excessive expansion or misallocation of resources.

Overall, while the majority of universities show SE scores above 0.85, there exists a noticeable “efficiency gap” in the midrange—specifically, a cluster of institutions with SE values between 0.6 and 0.7. This reflects an ongoing structural challenge among architecture universities, particularly in aligning institutional scale with effective resource deployment under the Green Campus development agenda.

3.3. College Classification

To systematically identify the efficiency characteristics of architecture universities in terms of resource utilization and scale configuration, this study classifies the 28 sampled institutions based on the DEA model results across four dimensions: Technical Efficiency (TE), Pure Technical Efficiency (PTE), Scale Efficiency (SE), and Returns to Scale (RTS). The classification criteria are as follows:

Fully Efficient Institutions: TE = 1, PTE = 1, SE = 1, and RTS = “CRS”, indicating operation at an optimal scale with fully efficient resource use and management;

Managerially Efficient but Scale-Suboptimal Institutions: PTE = 1 and TE < 1, implying that management is effective, but overall efficiency is constrained by scale inefficiency;

Comprehensively Inefficient Institutions: PTE < 1 and TE < 1, indicating inefficiencies in both resource management and scale structure.

Based on the above criteria, the distribution of the 28 architecture universities is shown in Figure 5.

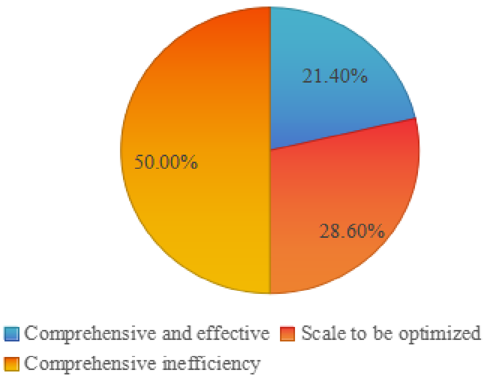


Fig. 5. Classification of Architecture Universities Based on DEA Results

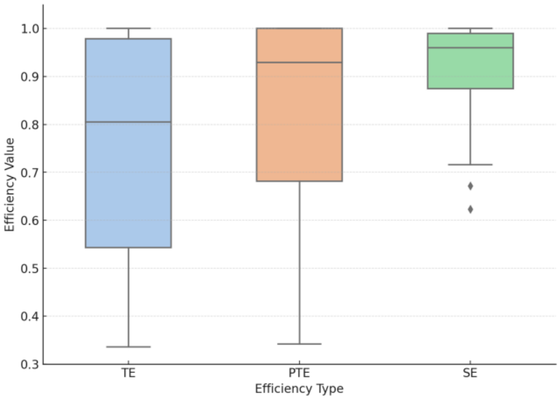


Fig. 6. Distribution of DEA Efficiency Scores

According to the calculation results, the following conclusions can be drawn. Comprehensively Inefficient Institutions account for 14 universities, representing 50% of the total sample and constituting the largest category. These institutions exhibit notable deficiencies in both management capacity and resource configuration. There is an urgent need for improvement across multiple dimensions, including teaching organization, resource allocation structure, and performance evaluation mechanisms. Representative examples include Chongqing University, Tongji University, and Zhejiang University. Managerially Efficient but Scale-Suboptimal Institutions include 8 universities, accounting for 28.6% of the total. These institutions demonstrate strong management performance, as reflected in a PTE score of 1, but their overall efficiency is limited by suboptimal scale structures. Notable examples include Tsinghua University and Tianjin University, where scale efficiency (SE) remains significantly below 1. These universities should consider adjusting their resource allocation or enrollment size based on their identified RTS type. Fully Efficient Institutions comprise 6 universities, making up 21.4% of the sample. These universities perform well across all three dimensions: management efficiency, resource utilization, and scale optimization, achieving the DEA-defined efficient frontier. Representative examples include Southwest Jiaotong University and Southeast University, which are expected to continue serving as models of excellence in promoting Green Campus initiatives and educational modernization.

Figure 6 illustrates the distribution of Technical Efficiency (TE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE) scores across the sampled universities. The results show that PTE values are generally high and tightly clustered, indicating strong managerial efficiency among most institutions. In contrast, TE and SE exhibit greater variability and lower medians, suggesting that overall efficiency is often constrained by scale-related issues. The presence of outliers in TE and SE further highlights disparities in resource utilization and scale optimization, underscoring the need for targeted improvements in resource allocation and campus planning.

4. Recommendations

With the continuous advancement of China’ s dual-carbon strategy and the promotion of green campus initiatives, the efficiency of educational resource allocation in universities has become central to achieving sustainability. DEA analysis reveals that some architecture universities suffer from input redundancy and scale inefficiency, exposing structural imbalances in traditional expansion-oriented resource allocation models. To promote a green transformation, universities should integrate low-carbon and environmentally friendly principles into resource investment strategies. This includes optimizing teaching spaces, faculty structure, and technological platforms toward energy-efficient, compact, and intelligent configurations. Initiatives such as modular classrooms, virtual learning systems, and shared laboratories can enhance resource reuse and reduce unit-level energy consumption.

In addition, green performance indicators—such as energy consumption, carbon emissions, and space utilization—should be incorporated into resource evaluation systems. A comprehensive metric framework that balances both educational output and ecological input will guide the transition from “quantitative expansion” to “green efficiency.” As pioneers of sustainable design, architecture universities are particularly well-positioned to lead this transformation and set benchmarks for future campus operations. Efficiency and sustainability should not be treated separately. Traditional DEA models often ignore environmental performance during resource use. By incorporating green metrics – like space utilization, energy intensity, and emissions – into efficiency assessments, universities can better align their operations with low-carbon goals. A data-driven feedback system that tracks resource and energy performance can support smarter, greener decision-making in campus planning and management.

Based on the DEA efficiency classification, differentiated and sustainability-oriented development strategies should be adopted for universities with varying performance profiles. For fully efficient institutions, efforts should focus on maintaining leadership by deepening green campus governance. These universities can serve as models by integrating green architecture, smart operations, and low-carbon education into a comprehensive system, and by contributing to regional or national standards for green campus development. Managerially efficient but scale-suboptimal institutions should prioritize structural refinement. Adjustments to enrollment size, academic discipline distribution, and spatial configuration can help align educational output with ecological input. Particularly, institutions identified with increasing or decreasing returns to scale (RTS) should avoid inefficient expansion and optimize their resource scale accordingly. Comprehensively inefficient institutions should adopt a green restructuring strategy. This includes consolidating underused resources, retrofitting inefficient buildings, and improving management mechanisms to address both overinvestment and managerial weaknesses. Transitioning from a high-input, low-output model to a more compact and green operational mode is key to long-term improvement.

Such a classification-based approach not only enhances resource efficiency but also provides a practical reference for policy-making and green governance in higher education. Under the guidance of sustainability goals, universities can formulate adaptive optimization pathways and build a system that balances educational outcomes with environmental responsibility.

5. Conclusions

Against the backdrop of China’s dual-carbon strategy and the continuous advancement of Green Campus initiatives, the efficient allocation of educational resources in universities has become a critical issue for achieving sustainability in higher education. This study evaluates the operational efficiency of 28 architecture universities by constructing a multi-input, multi-output DEA model, using indicators such as faculty size, teaching space, and student population as inputs, and employment rate, postgraduate enrollment, and architecture-related employment proportion as outputs. The analysis covers technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE), and further classifies institutions based on efficiency structure.

The results indicate that most universities exhibit high PTE scores, reflecting effective internal management and resource organization. However, significant variation in TE and SE suggests that overall efficiency is often limited by scale mismatches and structural imbalances. Classification results show that over half of the universities fall into the "comprehensively inefficient" or "scale-inefficient" categories, indicating a pressing need for resource restructuring, scale adjustment, and reform of performance evaluation systems with a sustainability focus.

This study also demonstrates the flexibility and practical value of DEA in evaluating educational performance, especially under the green development agenda. DEA can serve as a data-driven tool for optimizing resource use, guiding space utilization, and informing green governance. With the integration of ecological indicators, future research could explore green input‑output DEA models to further support sustainability assessments in higher education. In summary, this study provides a quantitative assessment of resource efficiency among architecture universities and offers theoretical and empirical support for promoting green transformation. The findings contribute to the ongoing efforts toward sustainable development, efficient resource governance, and modernization of higher education management in China.

While the current study applies a deterministic DEA framework based on available cross-sectional data, future studies could consider uncertainty and variability in educational environments. In real-world applications, input‑output data may be affected by policy shifts, incomplete records, or dynamic operational conditions. These factors highlight the need for more resilient models that can adapt to uncertainty and assess efficiency in a more robust manner. Recent research has begun to integrate fuzzy logic, neural inference, and robust optimization into DEA models, as seen in scenario-based studies in industrial systems [35]. Drawing from such approaches, future work could explore the potential of robust DEA (RDEA) or fuzzy DEA frameworks to evaluate educational performance under uncertainty, especially within the context of long-term sustainability goals and dynamic campus transformations.

Author Contributions

Conceptualization, Y.P. and MK.; methodology, Y.P.; software, Y.P.; validation, Y.P., M.K. and W.Z.; formal analysis, Y.P.; investigation, Y.P.; resources, Y.P.; data curation, Y.P.; writing–original draft preparation, Y.P.; writing–review and editing, A.M.F.-F.; visualization, W.Z.; supervision, A.M.F.-F.; project administration, A.M.F.-F. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Data Availability Statement

The data supporting the findings of this study are available from publicly accessible sources, including official university websites, annual employment reports, and the Ministry of Education’s statistics platform. No new data were created in this study.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was not funded by any grant.

Appendix A

Table A1
Original values of main variables

Name of college	Teaching Area (10k m^2)	Faculty (People)	Students (People)	Employment Rate (%)	Architecture Job (%)	Postgraduate Rate (%)
Tsinghua Univ.	198.1	132	1332	98.01	3.30	35.40
Tongji Univ.	184	258	2625	97.14	4.06	21.92
Southeast Univ.	78.9	169	1800	96.51	5.60	50.56
Tianjin Univ.	410.7	148	1760	94.86	11.18	55.18
SCUT	294	123	1734	98.31	4.25	24.55
Chongqing Univ.	160	726	8647	93.13	15.21	26.03
HIT	251.8	181	1950	97.04	8.21	29.98
SWJTU	75	120	1400	96.61	23.90	40.83
Central South Univ.	276	140	1900	95.68	7.46	31.89
Wuhan Univ.	222	124	1000	92.13	6.10	32.98
Zhejiang Univ.	462	313	1961	93.68	2.17	29.36
BUCEA	48.8	137	1850	96.45	41.07	19.97
SDAU	70	143	1533	96.31	42.06	24.48
AHJZU	102	91	1050	91.56	28.71	19.61
Fuzhou Univ.	171	64	880	85.34	8.89	32.22
Chang'an Univ.	119.3	157	2530	92.40	34.69	29.59
Hunan Univ.	134	115	1110	92.29	7.63	21.84
HEBUT	87	129	1700	90.08	22.57	27.10
Nanjing Tech	266.6	112	1400	91.18	22.73	31.62
KMUST	130	173	2000	82.56	22.50	15.36
Shenzhen Univ.	200.7	157	980	95.01	3.83	31.13
Suzhou Univ. Sci. & Tech	60	130	1400	94.10	12.77	17.4
TYUT	169	234	2500	90.07	9.32	26.51
SJZU	52	140	1450	86.68	58.18	22.29
Jilin Jianzhu Univ.	45.4	90	800	84.07	67.79	5.47
IMUT	97.2	102	978	80.05	8.59	12.17
Guangxi Univ.	133.1	217	3386	85.81	7.08	26.80
XAUAT	90	255	3012	90.38	35.62	19.84

References

[1] Fissi, S., Romolini, A., Gori, E., et al. (2021). The path toward a sustainable green university: The case of the University of Florence. Journal of Cleaner Production, 279, 123655. https://doi.org/10.1016/j.jclepro.2020.123655

[2] Tagliabue, L. C., Cecconi, F. R., Maltese, S., et al. (2021). Leveraging digital twin for sustainability assessment of an educational building. Sustainability, 13(2), 480. https://doi.org/10.3390/su13020480

[3] Li, Y., Chen, H., & Yu, P. (2024). Green campus transformation in smart city development: A study on low-carbon and energy-saving design for the renovation of school buildings. Smart Cities, 7(5), 2940–2965. https://doi.org/10.3390/smartcities7050115

[4] Kaan, M., Bozkurt, A., Genç, M. S., et al. (2024). Optimization study of an energy storage system supplied solar and wind energy sources for green campus. Process Safety and Environmental Protection, 190, 863–872. https://doi.org/10.1016/j.psep.2024.07.066

[5] Zheng, N., Li, S., Wang, Y., et al. (2021). Research on low-carbon campus based on ecological footprint evaluation and machine learning: A case study in China. Journal of Cleaner Production, 323, 129181. https://doi.org/10.1016/j.jclepro.2021.129181

[6] Ribeiro, J. M. P., Hoeckesfeld, L., Dal Magro, C. B., et al. (2021). Green Campus Initiatives as sustainable development dissemination at higher education institutions: Students' perceptions. Journal of Cleaner Production, 312, 127671. https://doi.org/10.1016/j.jclepro.2021.127671

[7] Rusli, N., Hussain, M. R. M., Nizarudin, N. D., et al. (n.d.). The implications of epistemology on knowledge and awareness in green campus management. [Journal name and other details missing]

[8] Hao, J., Ye, X., Yu, C., et al. (2023). A novel individual carbon emission evaluation and carbon trading model for low-carbon university campuses. Sustainability, 15(22), 15928. https://doi.org/10.3390/su152215928

[9] Sun, X., Gao, W., Zhao, M., et al. (2024). Optimize green campus sustainable construction from users' perspective. Environment, Development and Sustainability, 1–34. https://doi.org/10.1007/s10668-024-04580-y

[10] Güven, A. F., Yörükeren, N., & Samy, M. M. (2022). Design optimization of a stand-alone green energy system of university campus based on Jaya-Harmony Search and Ant Colony Optimization algorithms approaches. Energy, 253, 124089. https://doi.org/10.1016/j.energy.2022.124089

[11] Chen, C., Guo, B. R., Liu, S. Q., et al. (2024). Strategies for developing low-carbon university campuses in China within the context of sustainable development. [Journal name missing]. https://doi.org/10.22161/ijebm.8.4.5

[12] Na, W., & Zhao, Z. C. (2021). The comprehensive evaluation method of low-carbon campus based on analytic hierarchy process and weights of entropy. Environment, Development and Sustainability, 23, 9308–9319. https://doi.org/10.1007/s10668-020-01025-0

[13] Liu, H. Y., & Lee, H. C. (2022). The carbon inventory of the reuse phase's life cycle: The example of the reconstruction of a zero-carbon campus on an unused military camp. Sustainability, 14(3), 1064. https://doi.org/10.3390/su14031064

[14] Jiang, Y., Liu, W., Wang, F., et al. (2023). Low-carbon transformation of Nankai Campus based on energy audits comprehensive utilization of new energy. In E3S Web of Conferences, 406, 02029. https://doi.org/10.1051/e3sconf/202340602029

[15] Boarin, P., Martinez-Molina, A., & Juan-Ferruses, I. (2020). Understanding students' perception of sustainability in architecture education: A comparison among universities in three different continents. Journal of Cleaner Production, 248, 119237. https://doi.org/10.1016/j.jclepro.2019.119237

[16] El-Kholei, A. O., Amer, A. S., & Yassein, G. A. (2025). Embedding sustainable development goals in architectural education: A case study of Menoufia University 2023 graduation projects. Archnet-IJAR: International Journal of Architectural Research, 19(1), 149–170. https://doi.org/10.1108/ARCH-12-2023-0326

[17] Ng, V., Mari, T. S., & Lin, C. L. (2022). Re-thinking architecture education: Conceptualising curriculum through the lens of 21st century graduate attributes. Journal of Design and Built Environment, 22(2), 85–92. https://doi.org/10.22452/jdbe.vol22no2.6

[18] Mohamed, A. S., & Ibrahim, V. A. R. (2024). Towards a sustainable future: Exploring the integration of architecture education, innovation and sustainability. SVU-International Journal of Engineering Sciences and Applications, 5(1), 49–63. https://doi.org/10.21608/svusrc.2023.224923.1143

[19] Krajčo, K., Habánik, J., & Grenčíková, A. (2024). DEA models as a tool for evaluating and measuring the efficiency of public universities. Economics & Sociology, 17(1), 166–181. https://doi.org/10.14254/2071-789X.2024/17-1/11

[20] Chen, K., Wupur, A., Liu, X., et al. (2024). Measuring multiple-path technology transfer efficiency in Chinese universities: A network DEA-Tobit approach. Journal of the Knowledge Economy, 1–30. https://doi.org/10.1007/s13132-024-01971-4

[21] Maral, M., & Çetin, M. (2024). Teaching, research, and third mission efficiency of universities: A data envelopment analysis and hybrid multi-criteria decision-making approach. Managerial and Decision Economics, 45(4), 2171–2188. https://doi.org/10.1002/mde.4131

[22] Almeida, J. P. L., Anjos, F. H., Moreira, M. F., et al. (2025). University efficiency evaluation using data envelopment analysis: Future research agenda. Cogent Education, 12(1), 2445964. https://doi.org/10.1080/2331186X.2024.2445964

[23] Salas-Velasco, M. (2024). Evaluation of undergraduate academic programs through data envelopment analysis and time-to-degree estimates at Spanish public universities. Socio-Economic Planning Sciences, 93, 101878. https://doi.org/10.1016/j.seps.2024.101878

[24] Liu, C. Y. A., & Tsai, C. C. K. (2014). Evaluation on higher education using data envelopment analysis. International Journal of Management Excellence, 4(2), 522–528. https://doi.org/10.17722/ijme.v4i2.188

[25] Sun, Y., Wang, D., Yang, F., et al. (2023). Efficiency evaluation of higher education systems in China: A double frontier parallel DEA model. Computers & Industrial Engineering, 176, 108979. https://doi.org/10.1016/j.cie.2023.108979

[26] Xiong, X., Yang, G., Zhou, D., et al. (2022). How to allocate multi-period research resources? Centralized resource allocation for public universities in China using a parallel DEA-based approach. Socio-Economic Planning Sciences, 82, 101317. https://doi.org/10.1016/j.seps.2022.101317

[27] Laporte, J. P., & Cansino, J. M. (2024). Energy consumption in higher education institutions: A bibliometric analysis focused on scientific trends. Buildings, 14(2), 323. https://doi.org/10.3390/buildings14020323

[28] Zhao, H., Xu, Y., Hong, W. C., et al. (2021). Smart evaluation of green campus sustainability considering energy utilization. Sustainability, 13(14), 7653. https://doi.org/10.3390/su13147653

[29] Shuqin, C., Minyan, L., Hongwei, T., et al. (2019). Assessing sustainability on Chinese university campuses: Development of a campus sustainability evaluation system and its application with a case study. Journal of Building Engineering, 24, 100747. https://doi.org/10.1016/j.jobe.2019.100747

[30] Baricco, M., Tartaglino, A., Gambino, P., et al. (2018). University of Turin performance in UI GreenMetric energy and climate change. In E3S Web of Conferences, 48, 03003–03003. https://doi.org/10.1051/e3sconf/20184803003

[31] Zhu, B., & Liu, G. (2025). The development model of sustainable campus based on green buildings: A systematic comparative study between Japan and China. Engineering, Construction and Architectural Management, 32(2), 805–823. https://doi.org/10.1108/ECAM-03-2022-0236

[32] Chen, X., & Xia, W. (2022). Research on the strategy of resource saving campus construction under the green idea. The Frontiers of Society, Science and Technology, 4(7). https://doi.org/10.25236/FSST.2022.040702

[33] Guo, M., Zhu, Y., & Xu, A. (2024). Research on green campus evaluation in cold areas based on AHP-BP neural networks. Buildings, 14(9), 2792. https://doi.org/10.3390/buildings14092792

[34] Zou, Y., Zhong, N., Chen, Z., et al. (2024). Bridging digitalization and sustainability in universities: A Chinese green university initiative in the digital era. Journal of Cleaner Production, 469, 143181. https://doi.org/10.1016/j.jclepro.2024.143181

[35] Gholizadeh, H., Fathollahi-Fard, A. M., Fazlollahtabar, H., et al. (2022). Fuzzy data-driven scenario-based robust data envelopment analysis for prediction and optimisation of an electrical discharge machine's parameters. Expert Systems with Applications, 193, 116419. https://doi.org/10.1016/j.eswa.2021.116419