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ASSESSING REGIONAL DISPARITIES: A TYPOLOGY AND EFFICIENCY BENCHMARK OF UZBEKISTAN'S RAILWAY NETWORK

Summary. This paper presents an integrated principal component analysis, k-means, and data envelopment analysis workflow for regional railway benchmarking under limited data conditions. Principal component analysis reduces correlated socio-economic and infrastructure indicators to a small number of independent components, k-means then forms structurally comparable regional typologies, and an output-oriented CCR DEA model benchmarks infrastructure intensity efficiency, defined as the ability to convert socio-economic capacity into railway density. The methods are well established, and the novelty lies in their stepwise integration into one practical framework and their application in a developing country where detailed operational rail data are limited. The framework is demonstrated in 14 regions of Uzbekistan (2013–2022) and reveals clear typologies and large efficiency gaps. Compact or corridor-positioned regions define the frontier, while several large, capital-intensive territories remain far from best practice outcomes under the selected output measure. The results support typology-based planning and targeted investment priorities, and the workflow is transferable to other corridor and regional railway contexts.

1. INTRODUCTION

As a double landlocked country, Uzbekistan's railway network is not only infrastructure, but it is the cornerstone of its national economy and a critical bridge for Eurasian trade [1]. The nation's strategic location is central to major geopolitical transport projects, including the Trans-Caspian International Transport Route, or Middle Corridor, and the new China-Kyrgyzstan-Uzbekistan (CKU) railway, which is already under development [21].

When these new lines become operational, Uzbekistan's transit volume is expected to increase significantly, positioning it as a key logistics hub connecting Asia and Europe. This presents a massive opportunity, but it also exposes a core development challenge.

The problem is that Uzbekistan's current railway network already exhibits significant regional disparities in performance, density, and connectivity. It is unclear if the existing network is prepared for this new expected volume, or if massive state investments will translate into balanced, efficient regional growth. Before new capacity is added, it is essential to have a data-driven baseline for determining which regions are performing efficiently and which are lagging.

While many studies have assessed transport efficiency, most have done this at a national level, or they have focused on specific assets [2, 3]. A gap exists in providing a holistic, regional-level assessment that both classifies regions by their structural type and benchmarks their relative efficiency.

This paper fills this gap by developing a multi-stage quantitative framework to evaluate Uzbekistan's regional railway sector. The study integrates principal component analysis (PCA) to reduce the complexity of regional indicators, k-means clustering to classify regions into distinct typologies, and

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data envelopment analysis (DEA) to benchmark the efficiency of each region. The resulting framework intends to provide a clearer, data-driven tool for policymakers to identify high-performing benchmark regions and target inefficient regions for strategic investment.

The remainder of this paper is structured as follows: Section 2 reviews the literature on PCA, clustering, and DEA in transport analysis and in general. Section 3 details the data and the integrated three-stage methodology. Section 4 presents the results of the regional classification and efficiency benchmarking. Section 5 discusses the policy implications for each regional cluster, and Section 6 concludes the paper.

2. LITERATURE REVIEW

Assessing railway performance is complex because it depends on many interrelated drivers, including economic output, population density, spatial structure, and the physical characteristics of the network [4]. For this reason, recent research has increasingly used quantitative methods that can reduce complex datasets into understandable dimensions and benchmark performance consistently across comparable units. Such approaches are especially valuable when policymakers must allocate limited investment across regions with very different geographic and socio-economic conditions.

In Uzbekistan, earlier studies have applied multi-criteria and statistical approaches to capture regional differences in railway development and demand. One study used the analytical hierarchy process (AHP) to examine how socio-economic factors shape passenger rail demand. Another study compared traditional regression and machine learning models for freight forecasting and identified GDP and railway length as key predictors. More recently, PCA was used to develop a Railway Sector Capability Index (RSCI), highlighting persistent regional disparities in infrastructure and development potential. Together, these studies provide an empirical basis for understanding Uzbekistan's railway sector and show that regional variation is substantial and policy-relevant [5–7].

However, most of this work is mainly descriptive or predictive. It explains differences and forecasts trends, but it does not directly answer a practical policy question: which regions use their available resources more effectively, and which regions lag behind? The current research advances this line of work by introducing DEA as a non-parametric frontier method that measures efficiency directly and supports benchmarking among regions. In other words, the analysis not only describes capacity but also evaluates how well each region converts socio-economic inputs into observable railway infrastructure outcomes. This makes the results more actionable for planning and investment prioritization.

Recent research [8] emphasized that infrastructure inefficiency in railway systems is often driven not by a lack of rolling stock but by capacity constraints and coordination problems between mainline and private sidings, especially under market conditions. In this context, existing approaches highlight the importance of evaluating infrastructure occupation and transfer capacity as key determinants of overall railway performance.

To simplify high-dimensional datasets, researchers frequently employ PCA. PCA transforms a set of correlated variables into a smaller set of uncorrelated principal components, which represent the main underlying dimensions of variation. In transport and railway research, it has been used to identify latent factors that impact rail competitiveness [9], to reduce the complexity of railway maintenance and condition data [10, 11], and to aggregate diverse indicators into composite measures for evaluating carrying capacity and system capability [4]. These examples show that PCA is a strong first step for building robust inputs and avoiding redundancy when many indicators overlap.

Once the dataset is simplified, DEA is widely used to measure the relative efficiency of comparable entities, known as decision making units (DMUs). The transport literature shows DEA's flexibility across scales. At the micro level, capacity constraints have been examined through station-based analyses using statistical observation data, demonstrating how local processing limits and stochastic demand affect network performance [12]. Such studies illustrate how meaningful efficiency assessments can be conducted even when operational data are limited and heterogeneous. At the macro level, it has been applied to compare national railway systems across countries [2] and to benchmark the Belt and Road Initiative's transport performance [1]. At the micro level, DEA has been used to evaluate freight undertakings [13], inland intermodal terminals [3], and passenger railway stations [14]. This range demonstrates that DEA is suitable both for whole-system comparisons and more focused infrastructure and operational benchmarking.

The literature also discusses which DEA model is most appropriate. One line of research recommends a variable returns to scale (VRS/BCC) model when DMUs vary strongly in size because it separates pure technical efficiency from scale effects [15]. Other studies apply a CRS/CCR model to benchmark all DMUs against a single best-practice frontier [2]. This study adopts the CRS/CCR approach because it provides a clear unified benchmark and supports the policy goal of identifying regions that are farthest from best-practice performance under common assumptions. At the same time, the choice is interpreted carefully in light of Uzbekistan's notable geographic differences, as large and low-density regions may face natural scale constraints.

Recent "best practice" methodologies increasingly combine these techniques rather than using them in isolation. One integrated framework applies PCA before DEA to reduce the number of correlated inputs [16]. Another extends this idea by combining PCA, DEA, and clustering to identify benchmark groups and improve interpretability [17]. Similar integrated PCA-DEA and PCA-DEA-VIKOR approaches have also been successfully applied in other complex systems to improve robustness and avoid bias caused by multicollinearity and structural heterogeneity [24-26]. This integrated (PCA-clustering-DEA) structure is the approach adopted in this paper. It is particularly useful for Uzbekistan because regions differ not only in performance but also in structural type (e.g., the capital region versus large peripheral territories), so benchmarking without typologies can be misleading.

Despite the global growth of these integrated methods, a focused, data-driven efficiency assessment of Uzbekistan's regional railway system remains limited, especially when viewed against the backdrop of emerging international transport corridors and the rising importance of east-west connectivity. This study addresses this gap by first creating a regional typology using PCA and k-means clustering and then applying DEA to measure efficiency within that structured context. The outcome is a benchmarking framework that helps identify which regional types are performing well, where inefficiencies are concentrated, and where investment and operational attention may generate the highest returns.

3. METHODS

This study adopts a three-stage quantitative framework to analyse regional railway development and performance in Uzbekistan. First, PCA is used to reduce a set of correlated socio-economic and infrastructure indicators into a small number of independent components that capture the main structural dimensions of regional development. Second, k-means clustering is applied to the PCA scores to classify regions with similar development profiles into groups, allowing for the identification of comparable regional typologies. Third, DEA is employed to benchmark relative performance by evaluating how efficiently regions transform socio-economic capacity into railway infrastructure intensity.

By combining multivariate structural profiling (PCA and clustering) with efficiency benchmarking (DEA), the proposed framework distinguishes between differences arising from regional development structure and differences related to performance relative to best practices. This integrated approach allows the study to identify not only which regions are structurally advantaged or constrained but also which regions underperform or excel given their development context.

3.1. Data description, variable selection, and data normalization

The dataset covers 14 administrative regions of Uzbekistan from 2013-2022 using official statistical indicators. Data were sourced from the Statistical Yearbook of the Republic of Uzbekistan (2023) [18]. Initially, 13 indicators were collected to represent key drivers of railway development, including demographic characteristics, economic performance, industrial activity, investment conditions, and infrastructure and spatial context.

Pearson correlation matrices were calculated for each year and averaged across the full study period (2013-2022) to reduce redundancy and multicollinearity before multivariate analysis. The resulting average correlation heatmap (Fig. 1) reveals strong, persistent overlaps between several variables—particularly, between total population and employed population and between total capital investment and size-related economic indicators.

Based on this diagnostic, three variables (total population, employed population, and total capital investment) were excluded from the PCA and clustering stage. These variables primarily reflect regional scale and largely duplicate information captured by retained intensity-based indicators. In contrast, employment rate, population density, and investment per capita provide more informative measures of labor engagement, spatial concentration, and capital intensity that are less dominated by region size.

After this screening, a final set of ten representative variables was retained for PCA and clustering. These variables jointly capture economic capacity and productivity, industrial and market activity, labor intensity, spatial concentration, and infrastructure scale and intensity. All selected variables were non-negative and logically consistent, ensuring suitability for subsequent clustering and DEA analysis.

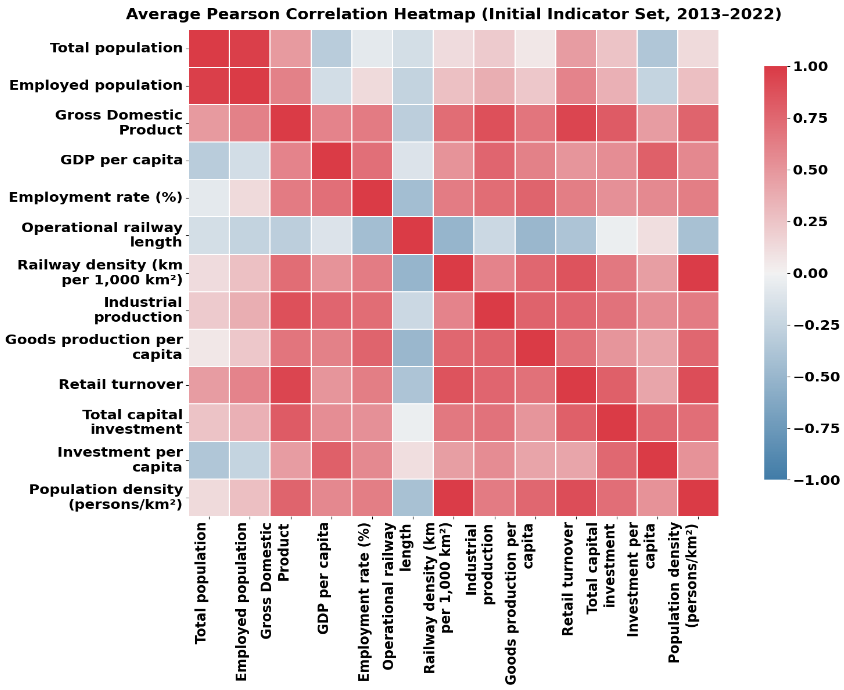

Fig. 1. Average Pearson correlation heatmap for the initial indicator set (2013-2022) used to identify persistent redundancy and support variable reduction for PCA and clustering

3.2. Structural profiling and regional typology: PCA and k-means clustering

This part of the study describes and classifies Uzbekistan's regions according to their overall development profiles relevant to railway transport. The objective is not to measure efficiency but to identify latent structural patterns such as economic capacity, industrial and market activity, labor intensity, spatial concentration, and infrastructure provision and to group regions into comparable typologies. Because regional socio-economic indicators are typically correlated, multivariate methods are required to avoid interpreting multiple overlapping variables separately.

For PCA and clustering, a broader set of indicators is required in order to represent all key dimensions of regional development Table 1. Prior to PCA, Pearson correlation matrices were computed for each year and averaged across 2013-2022 to produce an average correlation matrix. The resulting average correlation heatmap (Fig. 1) was used as a diagnostic tool to identify strong and stable overlaps among indicators and to support the selection of a representative variable set.

Table 1
Selected indicators for PCA and clustering: interpretation, assigned dimension, and relevance to railway development

Variables	Interpretation	Dimension (PCA)	Why it matters for railway development
Gross domestic product	Total regional economic output (economic scale)	Economic capacity and productivity	Higher economic scale is associated with greater passenger/freight potential and the ability to support transport development
GDP per capita	Economic output per person (productivity/wealth)	Economic capacity and productivity	Captures economic intensity and development level beyond sheer size
Industrial production	Industrial production (industrial base)	Industrial and market activity	Industrial output is a key driver of freight generation and logistics demand
Goods production per capita	Goods/production per capita (production intensity)	Industrial and market activity	Reflects production intensity adjusted for population; complements absolute industry production
Retail turnover	Retail turnover (consumption/market size)	Industrial and market activity	Represents regional market activity linked to both passenger mobility and distribution flows
Investment per capita	Investment per person (investment intensity)	Investment environment	Captures investment intensity and capital availability without being dominated by region size
Employment rate (%)	Employment rate (labor market intensity)	Demographic scale and labor capacity	Represents labor engagement and regional economic activity potential
Population density (persons/km²)	Population density (spatial concentration)	Demographic scale and labor capacity	Captures demand concentration and spatial feasibility of rail service provision
Operational railway length	Total length of operating railway lines	Infrastructure stock	Represents the existing scale of railway infrastructure inherited or developed over time
Railway density (km per 1,000 km²)	Railway density (infrastructure intensity outcome)	Infrastructure and spatial context	Intensity measure suitable for cross-region comparison and benchmarking

Based on this diagnostic, three variables (total population, employed population, and total capital investment) were excluded from the PCA and clustering stage because they largely duplicated information already captured by retained intensity-based measures. Specifically, total and employed population mainly reflect regional scale effects and show a high correlation with population density and employment rate, which better capture demand concentration and labor engagement. Similarly, total investment is strongly associated with regional economic size and overlaps with GDP-related indicators, while investment per capita provides a more informative measure of capital intensity. After this screening, a final set of ten non-redundant variables was retained for PCA and clustering. These variables jointly cover demographic and labor characteristics, economic and industrial activity, investment intensity, and railway infrastructure outcomes Table 1.

To simplify the 10 selected socio-economic and infrastructure indicators, we employed PCA, which is a statistical technique used to reduce the dimensionality of a dataset by identifying underlying patterns and transforming the original, correlated variables into a new set of uncorrelated variables called principal components (PCs) [19].

This PC1 score is calculated as a linear combination (a weighted sum) of the standardized indicators, as shown in the equation below:

$$\mathrm{PC}_1 = w_1^{(1)} z_1 + w_2^{(1)} z_2 + \cdots + w_{10}^{(1)} z_{10} \quad (1)$$

where:

z_j is the Z-score for indicator j,

$w_j^{(1)}$ is the PC1 loading (weight) for indicator j,

PC1 is a new variable representing the weighted sum of all indicators.

In this study, the first three principal components were retained for interpretation. The first component (PC1) broadly reflects an economic and industrial intensity dimension, driven by variables related to economic output, production activity, employment, and population concentration. The second component (PC2) captures an investment and infrastructure scale dimension and is associated mainly with investment per capita, GDP per capita, and operational railway length. The third component (PC3) highlights differences in railway network structure, particularly the balance between network size and spatial intensity. For clustering purposes, the first two components (PC1 and PC2) were treated as the main coordinates, as they represent the most important economic and infrastructure contrasts between regions.

To classify regions into meaningful groups, k-means clustering was applied to the PCA scores, mainly in the PC1-PC2 space [20]. The number of clusters was set to $k = 4$, supported by elbow and silhouette diagnostics, which indicated that three or four clusters provide a reasonable balance between separation and stability. The resulting clusters were interpreted using average indicator profiles, leading to clear regional typologies such as a dominant capital hub, industrial corridor regions, infrastructure-intensive regions, and less developed or low-density regions. This clustering step provides an interpretable spatial and economic segmentation of Uzbekistan's railway system and forms the basis for the subsequent efficiency analysis.

3.3. Efficiency assessment using output-oriented CCR DEA used in this study

DEA was then applied to evaluate how efficiently each region transforms its resources into railway infrastructure outcomes. Specifically, an output-oriented constant returns to scale model commonly known as the CCR model was implemented. This specification follows the original DEA framework, which measures efficiency relative to a best practice frontier constructed from the observed DMUs using linear programming [21]. At the same time, the CRS/CCR choice is consistent with established applications in transport efficiency benchmarking [13, 22]. The practical interpretation is straightforward: given a region's current resources, by how much could it proportionally expand railway infrastructure output without increasing inputs?

In this study, each region-year observation is treated as a DMU. DEA was estimated separately for each year (2013-2022) to ensure that regions are compared against peers operating under the same annual conditions, and the resulting efficiency scores were then summarized across years.

The input set represents economic capacity, industrial activity, investment intensity, and labor-market engagement. It includes gross domestic product, industrial production, investment per capita, and employment rate (%). The output variable is railway density (km per 1,000 km²), which captures the intensity of railway infrastructure normalized by area and, therefore, is suitable for cross-regional comparison.

The output-oriented CCR DEA model is formulated as follows.

Let regions be DMUs $j = 1, \dots, n$. For the evaluated region o, solve:

$$\max_{\phi,\lambda} \phi \tag{2}$$

subject to (inputs):

$$\sum_{j=1}^{n} \lambda_j \; Gross\ Domestic\ Product_j \leq Gross\ Domestic\ Product_o \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j \; IndustrialProduction_j \leq IndustrialProduction_o \tag{4}$$

$$\sum_{j=1}^{n} \lambda_j \; InvestmentPerCapita_j \leq InvestmentPerCapita_o \tag{5}$$

$$\sum_{j=1}^{n} \lambda_j \; EmploymentRate_j \leq EmploymentRate_o \tag{6}$$

(output):

$$\sum_{j=1}^{n} \lambda_j \; RailwayDensity_j \geq \phi \; RailwayDensity_o \tag{7}$$

$$\lambda_j \geq 0, \quad j = 1, \dots, n \tag{8}$$

Definitions:

- λ_j are nonnegative peer weights that construct a best-practice composite region from observed regions.

- $\phi \geq 1$ is the radial output expansion factor for region o, which is the largest proportional increase in railway density achievable without increasing any inputs (Pop, GDP, Industry_Prod, Inv), relative to the best-practice frontier under CRS.

Efficiency score:

$$\mathrm{EFF}_o = \frac{1}{\phi^*} \in (0,1] \tag{9}$$

Interpretation: If $\phi^* = 1.25$, then region o could increase rain density by 25% using the same inputs; its efficiency is $1/1.25 = 0.80$.

4. RESULTS

4.1. PCA results

The PCA applied to the selected socio-economic and infrastructure indicators reveals a clear low-dimensional structure of regional development patterns. The first three components explain approximately 84% of the total variance (PC1 = 63.2%, PC2 = 14.5%, PC3 = 8.9%), indicating that most regional differences can be captured by a small number of latent dimensions.

The component loadings in Fig. 2 show that PC1 is characterized by uniformly positive contributions from economic output, industrial production, market activity, labor engagement, population density, and railway density. This pattern indicates that PC1 represents a general economic and industrial intensity and spatial concentration dimension. Regions with high PC1 scores combine stronger production and consumption activity with denser population and railway infrastructure, reflecting a higher potential demand for and utilization of rail services.

PC2 contrasts per-capita economic and investment intensity with infrastructure scale. It is driven by strong positive loadings for GDP per capita and investment per capita, while operational railway length and population density contribute negatively. This component differentiates regions where development is driven by capital intensity and productivity from those characterized by extensive infrastructure spread over larger territories.

PC3 captures a secondary infrastructure and spatial scale dimension, with high loadings for operational railway length and retail activity. Although it explains a smaller share of variance, PC3 highlights differences in territorial coverage and network extent that are not fully reflected in the first two components.

For the purposes of regional typology, the first two components are retained for clustering, as they explain the majority of variation and provide a stable and interpretable representation of regional structural differences.

4.2. Regional typologies using k-means when k = 4

Using the first two principal components (PC1-PC2), k-means clustering was applied to identify groups of regions with similar structural characteristics relevant to railway development. The number of clusters was set to k = 4, based on inertia (elbow) and silhouette diagnostics, which indicated an acceptable balance between cluster separation and interpretability.

Fig. 3 presents the results of k-means clustering in the PC1-PC2 space. The spatial arrangement of regions confirms a clear structural differentiation across Uzbekistan.

One region, Tashkent City, is fully isolated along the positive side of PC1 and forms a single-member cluster. This separation reflects its exceptionally high economic intensity, population concentration, and railway infrastructure density compared to all other regions, justifying its treatment as a distinct capital-hub benchmark.

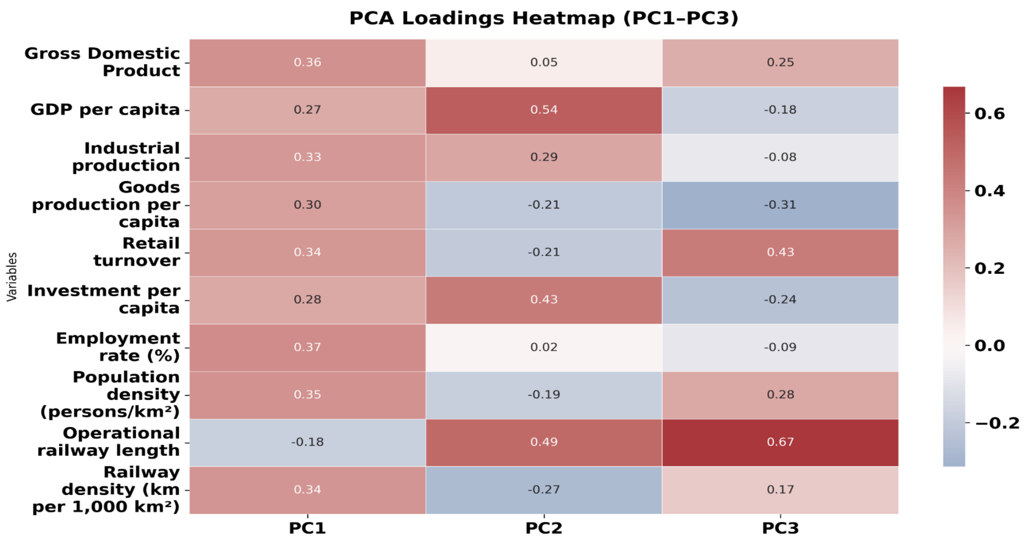

Fig. 2. PCA loadings for the selected indicators (PC1-PC3)

Note: Loadings indicate the contribution of each standardized indicator to the component. A higher absolute value implies a stronger influence. The sign indicates direction only (components may be multiplied by 1 without changing the model). PCA produces component scores for each region. Because the indicators were standardized (z-scores), component scores are centered around 0: positive scores indicate above-average alignment with the component, while negative scores indicate below-average alignment. Larger absolute values reflect stronger expressions of the component.

The remaining regions form three more compact clusters located closer to the origin or on the negative side of PC1. These clusters overlap partially in the PCA space but remain distinguishable, indicating that while regions may share some characteristics, their overall development profiles differ systematically. The positioning of regions within the PC1-PC2 plane confirms that clustering is driven by combinations of economic scale, industrial activity, spatial concentration, and infrastructure outcomes rather than by a single indicator.

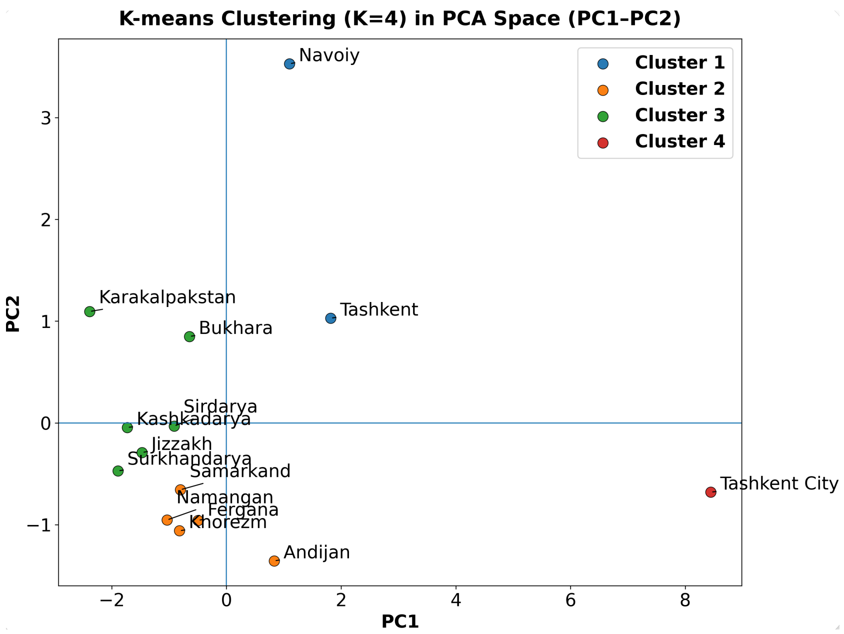

Fig. 3. PCA space and cluster separation

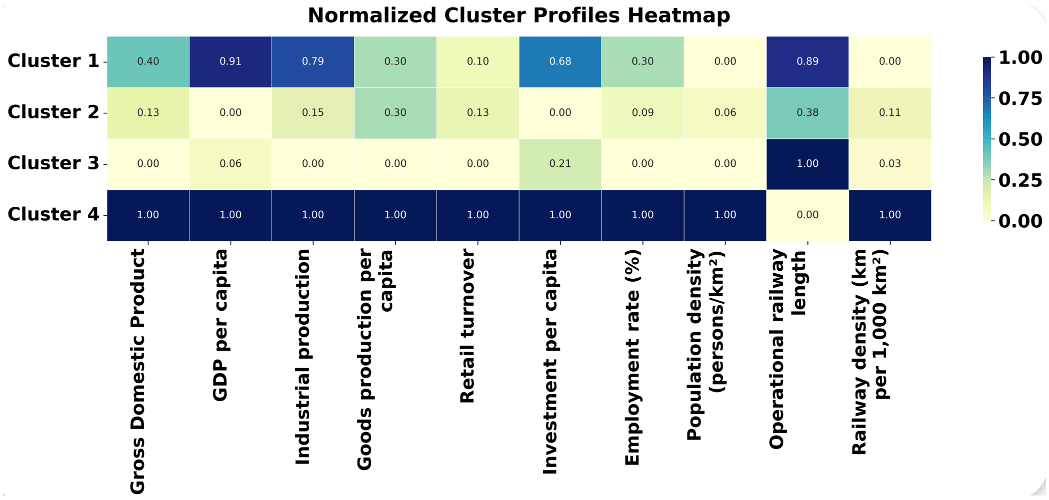

Fig. 4. Structural interpretation using normalized cluster profiles

While Fig. 3 shows where clusters lie in the reduced PCA space, Fig. 4 explains why these clusters differ. Fig. 4 presents normalized mean values (0-1 scaling) of the original indicators for each cluster, allowing direct comparison across variables with different units.

The profiles reveal four distinct development patterns:

- One cluster shows moderate values across most indicators, with relatively low railway density and weaker economic pressure. These regions can be described as balanced but developing. Infrastructure expansion may be constrained by demand and scale rather than by lack of resources alone.
- Another cluster displays high GDP and investment capacity but relatively low employment intensity and railway density. This pattern indicates capital-heavy regions, which have economic resources but have not fully translated them into rail infrastructure outcomes, possibly due to spatial dispersion or investment priorities outside the rail sector.
- A third cluster is characterized by high population density and industrial activity, with more balanced railway density levels. These regions are industrial corridor areas, where concentrated demand supports the effective use of rail infrastructure.
- The final cluster, consisting solely of Tashkent City, dominates all indicators simultaneously. Its profile confirms an extreme concentration of economic activity, population, and infrastructure, reinforcing its role as the national benchmark rather than a typical regional case.

Table 2

Regional typologies identified by k-means clustering (k = 4): main regions, key characteristics, and interpretation

Cluster	Main regions	Key characteristics	Interpretation
Cluster 1	Jizzakh, Khorezm, Surkhandarya, Karakalpakstan	Moderate economic activity, low infrastructure intensity	Balanced but developing regions
Cluster 2	Tashkent, Bukhara, Navoiy, Andijan	High GDP and investment, weak labor and rail intensity	Capital-heavy regions
Cluster 3	Namangan, Fergana, Samarkand	High population density and industrial activity	Industrial corridor regions
Cluster 4	Tashkent City	Extreme economic and infrastructure concentration	Capital hub and benchmark

To support interpretation and improve readability, the cluster results are summarized in Tab. 2, which lists the main regions in each cluster, their dominant characteristics, and a concise interpretation.

Retaining this table is recommended because it provides a compact narrative bridge between quantitative results (Figs. 3 and 4) and subsequent efficiency analysis using DEA.

The PCA and k-means results demonstrate that Uzbekistan's regions form structurally distinct typologies rather than following a single development gradient. These typologies provide the structural context for the DEA analysis that follows. In particular, they allow efficiency differences to be interpreted relative to comparable regional profiles rather than as isolated performance outcomes. The next section examines how efficiently regions within each cluster convert socio-economic capacity into railway infrastructure density.

4.3. DEA efficiency results

DEA was applied to evaluate how efficiently regions convert socio-economic capacity into railway infrastructure intensity. Efficiency scores based on an output-oriented CRS specification ranged from 0.11 to 1.00, with an average value of approximately 0.55, indicating substantial performance disparities across regions (Fig. 5).

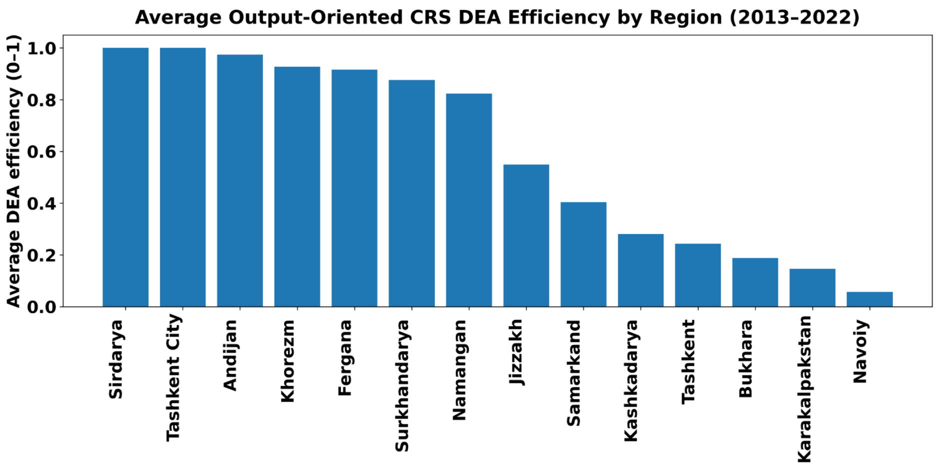

Fig. 5. Output-oriented CCR (CRS) DEA efficiency scores by region (1.0 = frontier/best practice)

Two regions (Tashkent City and Sirdarya) lie on the efficiency frontier, representing best-practice cases within the observed sample. Several other regions, including Khorezm and Jizzakh, also show relatively high efficiency, suggesting effective alignment between available resources and railway infrastructure outcomes.

In contrast, Navoiy, Bukhara, and Kashkadarya exhibit the lowest efficiency scores. Under an output-oriented interpretation, these results imply a considerable gap between existing railway density and the level that could be achieved given their socio-economic inputs. A likely explanation is their territorial scale and spatial dispersion, as large-area regions with low population density face higher costs and weaker demand concentration, which reduces measured efficiency under CRS assumptions.

These findings confirm that high economic capacity alone does not guarantee efficient railway development, particularly when spatial conditions are unfavorable.

4.4. DEA efficiency by cluster

A comparison of efficiency across the previously identified clusters (Fig. 6) reveals systematic differences. The capital cluster achieves full efficiency and serves as the reference frontier. Industrial corridor regions display moderate but stable efficiency, reflecting favorable demand concentration and utilization conditions.

Fig. 6 compares output-oriented CRS DEA efficiency across the four clusters identified earlier. Clear differences emerge in how regional groups convert socio-economic capacity into railway infrastructure outcomes.

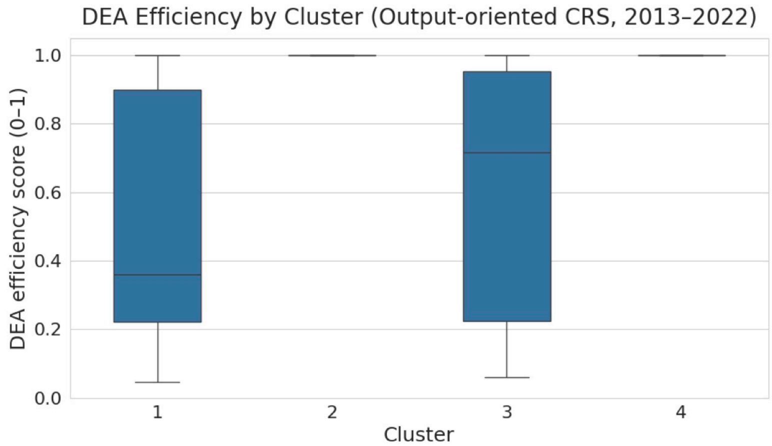

Fig. 6. Distribution of DEA efficiency scores by cluster (median and interquartile range), showing within-cluster variability

Cluster 4 (Tashkent City) reaches full efficiency (DEA = 1.00) and defines the efficiency frontier, confirming its role as the capital hub with highly concentrated economic activity and rail infrastructure.

Cluster 1 (balanced but developing regions) shows the largest variability in efficiency. While several regions perform poorly, Sirdarya attains frontier efficiency, demonstrating that high efficiency can be achieved without exceptional economic scale.

Cluster 3 (industrial corridor regions) records moderate and stable efficiency levels, supported by a population concentration and industrial activity that sustain rail utilization.

Cluster 2 (capital-heavy regions) exhibits generally low efficiency despite its relatively high GDP and investment levels, indicating that capital intensity alone does not ensure efficient railway outcomes under constant returns to scale.

Overall, the results show that structural strength and efficiency do not always coincide, underscoring the value of combining PCA-based typologies with DEA benchmarking to distinguish structural conditions from performance outcomes.

5. DISCUSSIONS AND RECOMMENDATIONS

This study combined PCA, k-means clustering, and DEA to examine regional railway development from both a structural and a performance perspective. Rather than relying on a single method, the framework first identifies underlying development patterns, then groups regions with similar characteristics, and finally benchmarks how efficiently those regions translate socio-economic capacity into railway infrastructure outcomes. This sequence helps avoid misleading comparisons between fundamentally different regions.

Within this framework, DEA is used to assess infrastructure intensity efficiency, defined as how effectively regions transform broad socio-economic capacity (population, GDP, industrial production, and total investment) into railway density. The efficiency scores, therefore, benchmark resource to network outcomes—not service quality, traffic volumes, or operational reliability, which are beyond the scope of the selected output. The results indicate relative structural comparisons rather than comprehensive evaluations of railway operations.

When interpreted together with PCA-based typologies, the DEA results reveal clear geographic and functional patterns across Uzbekistan. Regions are not homogeneous DMUs, as they differ substantially in their territory size, settlement structure, and role within the national railway system. This is most evident in Cluster 4 (Tashkent City), which consistently defines the efficiency frontier. Its compact urban form, high economic concentration, and dense rail network naturally produce very high railway density per area. For this reason, Tashkent City should be treated as a benchmark case rather than as a directly comparable peer.

At the other end, several capital-heavy but low-density regions, such as Navoiy and parts of Bukhara, exhibit relatively low DEA efficiency despite substantial economic capacity and investment. Under a constant returns to scale assumption, such regions appear inefficient because infrastructure must cover large territories and demand is spatially dispersed. This does not indicate poor policy or mismanagement; rather, it reflects scale and utilization constraints imposed by geography. In these contexts, expanding network length alone is unlikely to raise efficiency without parallel growth in stable rail demand.

The Fergana Valley regions (Andijan, Fergana, Namangan) occupy a different position. Their high population density and strong industrial base support intensive rail use, which explains their relatively strong performance. This finding gains additional importance in light of the planned China-Kyrgyzstan-Uzbekistan (CKU) railway, which is expected to connect to Uzbekistan through Andijan. Any increase in eastbound or westbound freight will depend heavily on the capacity and reliability of the Angren-Pap (Kamchik) corridor, a single-track mountain link with a long tunnel. As a result, efficiency in the valley cannot be separated from resilience and capacity at this national bottleneck.

Finally, Sirdarya illustrates that high efficiency is not limited to large or wealthy regions. Its strong DEA performance reflects a favorable corridor position and relatively simple network structure, highlighting the importance of network function and connectivity alongside economic scale.

Recommendations. First, Tashkent City should be treated as a special benchmark, not as a standard comparator. For planning and evaluation purposes, CRS-based results should be complemented by scale-adjusted approaches, and efficiency comparisons should primarily be made within similar regional typologies.

Second, capacity and operational resilience on the Angren-Pap corridor should be a national priority. With expected freight inflows from the CKU connection, system performance will increasingly depend on this single mountain crossing. Practical measures, such as passing loops, signaling upgrades, dispatching optimization, and passenger freight slot coordination, are likely to yield higher returns than large-scale new construction.

Third, dense and industrial regions (Andijan, Fergana, Namangan, Samarkand) should be prioritized for investments related to throughput and service quality, including terminal upgrades, yard capacity improvements, industrial sidings, and digital freight management. In these areas, demand conditions favor intensive infrastructure use.

Fourth, in large, low-density regions such as Navoiy and parts of Bukhara, policy should shift from “more track” toward “more use.” Emphasis should be placed on freight consolidation nodes, intermodal facilities, and industrial location strategies that can generate stable rail demand. Performance monitoring in these regions should rely less on network length and more on operational indicators such as throughput, wagon turnaround, and reliability.

6. CONCLUSIONS

This study shows that railway development performance in Uzbekistan is strongly shaped by regional structure, geography, and network role. By combining PCA, clustering, and DEA, the analysis distinguishes between structural conditions and relative efficiency, offering a more nuanced picture than single-method approaches.

The results demonstrate that high investment does not automatically lead to high efficiency in Uzbekistan, particularly in large and sparsely populated regions where utilization is constrained. At the same time, highly efficient cases such as Tashkent City and corridor-oriented regions like Sirdarya highlight how compactness, concentration of activity, and favorable network positioning can support infrastructure performance.

Looking ahead, the planned CKU connection reinforces the strategic importance of the Fergana Valley and the Angren-Pap mountain corridor. Because this section combines high future demand with physical constraints, Uzbekistan’s ability to benefit from growing transit flows will depend on maintaining capacity and reliability at this critical link.

Overall, the findings support a differentiated, cluster-based development strategy that involves optimizing throughput and reliability in dense regions, focusing on utilization and consolidation in low-density territories, and managing key corridors as national strategic assets. This approach aligns infrastructure investment more closely with regional realities and long-term system performance.

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