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# Optimizing Resource Efficiency and Operational Performance of Railway Terminals in Uzbekistan

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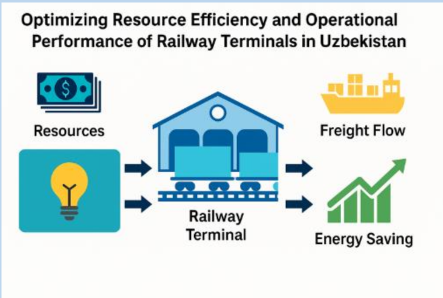
**Abstract:** Uzbekistan, a doubly landlocked country, relies extensively on its railway network for freight and passenger transport. Ensuring efficiency and reliability requires targeted investment in rail tracks, intermodal terminals, and modern equipment. This study investigatesthe resource efficiency and operational performance of railway terminals in Uz bekistan, focusing on key hubs in Tashkent and Navoi. A mixed-methods approach was employed, combining surveys with terminal operators, semi-structured interviews with railway managers, field observations, and statistical analyses using correlation and principal component analysis (PCA). The results reveal that bulk commodities such as coal, wood products, and flour products have the strongest positive correlation with total freight volume, while certain categories, including grain products and black metals, show negative correlations, suggesting distinct handling patterns and potential inefficiencies. Comparative analysis with Kazakhstan indicates that Uzbekistan's terminals handle a similar volume of bulk freight but lag in automation levels by approximately 15-20%. The study contributes by identifyingcommodity specific operational drivers, highlighting the need for targeted infrastructure upgrades, automation adoption, and strategic scheduling to optimize resource use. These findings offer actionable recommendations for policymakers and railway authorities seeking to enhance competitiveness and sustainability in landlocked regions.




**Keywords:** Railway Terminals, Operational Efficiency, Resource Utilization, Mixed-Method Approach, Operational Practices, Policy Frameworks, Energy Efficiency, Sustainability, Digitalization, Automation.

## Introduction

Railway networks are globally valued by policymakers and the public alike for enhancing mobility, optimizing urban land use, and offering a lower environmental footprint than road or air transport [1]. By reducing demands for parking and supporting transit-oriented development, efficient rail systems bolster both sustainability and economic vibrancy. Many governments are deeply invested in rail infrastructure both financially and strategically yet must also manage budgetary constraints, which heightens the importance of operational efficiency [2].

The effectiveness of a country's rail network depends on its geography, history, and governance structures [3,4]. For instance, Switzerland and Japan face steeper infrastructure costs due to mountainous terrain, while countries like Germany and Belgium benefit from high asset utilization owing to dense populations [5]. Landlocked nations, such as Uzbekistan, depend heavily on rail transport for economic connectivity and regional integration. In Uzbekistan, annual freight volumes have been growing steadily, but rail competes increasingly with road transport, which is expanding more rapidly (roughly 6.8 % p.a. vs. 2.4 % for rail between 2010–2019) [6].

This study builds upon our previous work [47], which applied correlation analysis to identify relationships between freight categories at Uzbek railway terminals. In contrast, the present paper extends that framework by integrating both correlation and principal component analysis (PCA) to identify latent operational factors influencing terminal performance and by incorporating a comparative evaluation with Kazakhstan's railway terminals. These methodological extensions allow for a more comprehensive assessment of resource efficiency and operational optimization strategies.

Comparative assessments, such as the CAREC Railway Sector Analysis, indicate that Kazakhstan achieves higher staff productivity, track density, and stock utilization than Uzbekistan, largely due to greater automation and targeted investment in key hubs like Dostyk and Khorgos [7]. This suggests that while Uzbekistan maintains strong throughput in bulk commodities, variability in handling times and limited automation create operational bottlenecks. Recognizing these gaps, the present study investigates how different freight categories influence overall terminal efficiency, examines the statistical relationships between cargo types and throughput using correlation and principal component analysis (PCA), and compares Uzbekistan's performance with Kazakhstan to identify actionable improvement areas.

By addressing these questions within the context of two key Uzbek terminals Tashkent and Navoi the research seeks to clarify which commodities drive or hinder resource efficiency, how statistical tools can reveal hidden operational patterns, and what lessons can be drawn from regional best practices.

## Key Definitions

For the purpose of this study:

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- Resource efficiency refers to the optimal use of labor, energy, and physical infrastructure to achieve the maximum possible freight throughput at the lowest input cost.
- Operational performance is defined as the ability of a terminal to handle freight volumes reliably, quickly, and without excessive delays, while maintaining quality and safety standards.
- Efficient railway terminals are essential nodes in the freight network, directly influencing cargo handling speed, cost, and reliability. Across the globe, strategies to enhance terminal performance focus on three interconnected dimensions: technological innovation, operational management, and supportive policy frameworks.

## Energy and Resource Efficiency

Energy use remains one of the largest cost drivers in rail operations. Studies in Europe and Asia show that optimizing traction energy, implementing regenerative braking, and deploying energy storage systems can reduce operating costs by 10- 20 % while lowering emissions [8,9]. For example, González Gil et al. [10] demonstrated that coordinated train scheduling combined with real-time driving assistance reduced urban rail energy consumption by up to 18 %. In heavy rail freight, optimal locomotive sizing and energy efficient driving patterns have shown measurable reductions in fuel consumption [11]. Recent works emphasize not only energy-saving driving patterns but also the integration of renewable sources into rail operations. For example, hybrid-electric locomotives powered partly by solar and wind energy have been piloted in China and Germany, achieving up to 25% additional savings in traction energy [39]. Similarly, large-scale regenerative braking projects in Japan demonstrate that surplus electricity can be redirected to nearby industrial consumers, creating a broader energy ecosystem beyond rail [40]. These findings suggest that Uzbekistan's energy optimization agenda could also benefit from renewable integration and sectoral synergies.

## Operational Performance and Automation

Operational performance at terminals is increasingly linked to the level of automation and digitalization. Process analyses of European marshalling yards, such as Hallsberg in Sweden, illustrate how automated shunting and digital traffic management reduce dwell times and improve safety [10]. Container terminals in Asia, including Shanghai and Busan, have adopted advanced yard cranes, automated guided vehicles, and AI-based scheduling, achieving throughput gains of 15- 25 % without significant land expansion [11]. Beyond yard automation, scholars highlight the role of predictive maintenance and AI-supported decision systems in enhancing terminal performance. A study of U.S. freight hubs indicates that predictive maintenance can reduce unplanned downtime of cranes and wagons by 20–30% [41]. In Europe, digital twins of terminals are increasingly used for scenario testing, allowing managers to simulate congestion patterns before they occur [42]. These approaches complement traditional automation by improving resilience and enabling proactive resource allocation.

## Material and Flow Efficiency

Resource efficiency also extends to the materials and infrastructure life cycle. Life Cycle Assessment (LCA) approaches reveal that using recycled aggregates in track bed construction can reduce raw material consumption by up to 30 % [12]. Data Envelopment Analysis (DEA) is widely applied to evaluate the relative efficiency of railway operators, comparing inputs like labor and fuel to outputs like ton kilometers [13]. Recent literature also points to the importance of circular economy principles in railway infrastructure. Studies in Italy and South Korea show that recycling steel sleepers and concrete ties reduces both raw material demand and lifecycle emissions while maintaining structural reliability [43]. Additionally, digital freight flow platforms, tested in Scandinavia, use blockchain-based documentation to reduce paperwork delays and ensure transparent tracking across borders [44]. These innovations demonstrate that material and flow efficiency requires both physical reuse and digital integration.

## Regional Context: Central Asia

In Central Asia, landlocked geography makes railway efficiency critical for trade competitiveness. Kazakhstan's investment in automated handling at Dostyk and Khorgos has cut container transfer times to under 3 hours, while Uzbekistan's main hubs still average 4–6 hours for similar volumes [14]. Meanwhile, Kyrgyzstan struggles with outdated yard equipment and limited ICT integration, which prolongs wagon turnaround times [15]. These examples highlight that modernization is not solely a matter of funding but also of strategic focus on bottleneck processes.

Recent literature (2024–2025) reinforces the link between terminal digitalisation and measurable efficiency gains. Sector reviews highlight that AI-enabled terminal and yard operating systems improve real-time visibility and planning, unlocking higher asset productivity and smoother wagon flows when paired with robust data foundations and APIs [32,34]. Empirical and technical studies on rail automation further document how interactions between automation and signalling, as well as IVG-based identification in yards, accelerate processes and reduce dwell times [34,35]. At the policy level, updates on Central Asia's rail agenda (including Uzbekistan) emphasise targeted investments and corridor upgrades, while industry surveys warn that digital readiness gaps still slow AI adoption in intermodal terminals [37]. Collectively, these works support our focus on selective automation and data-driven scheduling as near-term levers for Uzbek terminals.

Previous studies such as [47] mainly focused on correlation-based analysis of freight flow interactions in Uzbekistan's terminals. However, these approaches did not reveal the underlying structural components or cross-country differences in efficiency. The present study addresses this gap through PCA-based dimensional reduction and comparative benchmarking.

## Developed vs. Developing Countries

Comparative studies show clear contrasts between developed and developing countries in terms of terminal modernization and operational efficiency. In highly developed contexts such as Germany and Japan, investments in full automation, predictive analytics, and integrated ICT platforms have delivered measurable improvements in wagon turnaround times and cargo throughput [45]. By contrast, developing countries including India and Kazakhstan face constraints related to capital investment and workforce readiness, often relying on partial automation and incremental digital adoption [46]. These differences underscore that while best practices from advanced systems provide valuable guidance, developing economies must tailor modernization strategies to local institutional and resource realities.

## Case of Palestine

Relevant to the context of this journal, Palestine provides an example of a developing economy with constrained political and economic conditions. A recent assessment of cross-border connectivity highlights how landlocked and politically restricted systems require unique approaches to terminal management [47]. In Palestine, limited access to advanced equipment and infrastructure is offset by strategies such as prioritizing high-impact corridors, enhancing regional cooperation, and focusing on lowcost digital tools to maximize efficiency. Lessons from this case may inform Uzbekistan's railway modernization, especially given its own landlocked geography and regional dependence.

### Gap in the Literature

Existing research tends to focus either on macro-scale corridor efficiency or on infrastructure investment needs, but there is limited attention to commodity-specific operational patterns at the terminal level particularly in the Central Asian context. Understanding how different freight categories correlate with terminal performance can inform targeted interventions in scheduling, resource allocation, and automation investment. This study aims to fill that gap by combining statistical analysis with regional benchmarking.

## Materials and Methods

### Study Context

This research focuses on two major railway terminals in Uzbekistan Tashkent and Navoi which act as national and regional gateways for freight transport. These terminals handle a diverse mix of commodities, from bulk goods such as coal and grain to containerized industrial products. Their efficiency is critical to Uzbekistan's role in Central Asian trade corridors.

### Data Sources

The study draws on three main data streams:

1. Railway operator reports - Annual and quarterly statistics from Uzbekistan temir yo'llari, covering throughput, energy use, and operational metrics.
2. National transport statistics - Government datasets on cargo volumes, fuel consumption, and labor hours.
3. Field observations & Interviews - Direct timing of cargo handling processes, plus semi-structured interviews with terminal managers and operations staff to capture contextual factors not visible in raw data.

### SPSS Application for Data Processing

Once data has been collected, SPSS will be used for data processing, statistical analysis, and reporting. Data from reports, statistical records, and field studies will be entered into SPSS. The data can be imported from Excel formats into the SPSS database.

### Analytical Approach

A mixed- methods strategy was used, combining qualitative insights from interviews and field notes with quantitative statistical analysis.

1. Correlation Analysis - Pearson's correlation coefficients were used to identify relationships between cargo categories and total freight volume. This method was chosen for its ability to quickly highlight positive and negative associations, which can signal potential operational synergies or conflicts.
2. Principal Component Analysis (PCA) - PCA was applied to reduce the dimensionality of the dataset and group related variables into underlying components. This approach is particularly suited to freight data because it can reveal latent patterns-such as groups of commodities that tend to move together or require similar resources- without being distorted by variable scale differences.

Correlation identifies direct statistical relationships, useful for pinpointing where changes in one commodity's flow may affect overall terminal throughput. PCA, on the other hand, uncovers broader patterns and clusters that are not obvious in raw tables, helping to inform strategic operational planning.

### Correlation

The correlation analysis in this study relies solely on Pearson's correlation coefficient, which measures the strength and direction of linear relationships between variables. The test was applied to key operational indicators, including total freight volume, grain products, oil products, and construction materials, in order to identify which categories exhibit the strongest association with overall throughput. Only these variables and results are reported, as presented in Table 1.

Pearson's Correlation Coefficient (also called linear correlation): This is the most common type of correlation and measures the linear relationship between two continuous variables [23]. It assumes that the relationship between the variables is linear, and that the data is normally distributed. It is mostly denoted by r. The formula for the Pearson correlation coefficient between two variables $X$ and $Y$ is:

$$r = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{(X_i-\bar{X})^2(Y_i-\bar{Y})^2}} \tag{1}$$

Where:

$r$ is the Pearson correlation coefficient

$X_i$ and $Y_i$ are the individual data points for variables $X$ and $Y$ respectively

$\bar{X}$ and $\bar{Y}$ are the means of the variables $X$ and $Y$

n is the number of data points (sample size)

The value of the Pearson correlation coefficient ranges from -1 to +1. When $r = 1$, it indicates a perfect positive correlation, meaning that as $X$ increases, $Y$ also increases in perfect proportion [24]. Similarly, when $r = -1$, it signifies a perfect negative correlation, meaning that as $X$ increases, $Y$ decreases in perfect proportion. If $r = 0$, this means there is no linear relationship between the two variables; changes in $X$ do not correspond to consistent changes in $Y$.

Principal Component Analysis

Principal Component Analysis (PCA) is employed in this study as a dimensionality reduction technique to transform high-dimensional data into a lower-dimensional space while preserving the most significant variance in the dataset [27]. PCA enables the extraction of latent structures and patterns, thereby improving interpretability and computational efficiency without substantial loss of information.

### Mathematical Framework

Given a dataset $x$ consisting of observations and variables, PCA aims to derive a new set of orthogonal variables, termed principal components, that maximize the variance in the data. The steps involved in PCA are as follows:

**Standardization**: The data matrix $x$ is standardized to ensure that variables with different scales do not dominate the principal components. This is achieved using:

$$z = \frac{x-\bar{x}}{s} \tag{2}$$

where $\bar{x}$and $s$ denote the mean and standard deviation of each variable, respectively.

**Covariance Matrix Computation**: The covariance matrix $C$ of the standardized data is computed to capture the relationships between variables:

$$C = \frac{1}{n}z^T z \tag{3}$$

**Eigenvalue Decomposition**: The eigenvalues and corresponding eigenvectors of the covariance matrix are computed:

$$C = \tau_i v_i \tag{4}$$

Where $\tau_i$ represents the eigenvalues, and $v_i$ are the eigenvectors.

**Principal Component Selection**: The eigenvectors corresponding to the largest eigenvalues are selected as the principal components. The proportion of variance explained (PVE) by each component is given by:

$$PVE_i = \frac{\tau_i}{\sum_{j=1}^{p} \tau_j} \quad (5)$$

**Transformation**: The original data is projected onto the selected principal components to obtain the transformed data matrix:

$$x^* = zv_k \quad (6)$$

Where $v_k$ contains the top $k$ eigenvectors.

PCA is employed in this study for the following reasons:

**Reducing Dimensionality**: High-dimensional datasets often suffer from multicollinearity and computational inefficiency. PCA helps mitigate these issues by identifying the most informative features.

**Feature Extraction**: By transforming correlated variables into orthogonal components, PCA enhances interpretability while preserving the maximum variance.

**Noise Reduction**: PCA helps eliminate irrelevant variability in the data, improving the robustness of subsequent analyses.

By implementing PCA, this study ensures that the data retains its most informative characteristics while minimizing redundancy, thereby facilitating more efficient and accurate downstream analyses.

## Line Graph

A line graph is a visual representation of data where individual data points are connected by straight lines, often used to display trends over time or continuous variables [28]. The graph consists of two axes: the horizontal axis, typically representing the independent variable, and the vertical axis, which shows the dependent variable. Data points on the graph are plotted based on their corresponding values on these axes and are then connected by lines to illustrate changes, patterns, or relationships in the data.

Line graphs are particularly effective for showing trends or fluctuations. The line showing moves upward from left to right, it indicates an increase in the dependent variable over time, suggesting growth or improvement [29]. Conversely, a downward-sloping line represents a decline, while a flat line indicates little or no change, suggesting stability. A steeper slope reflects rapid change, while a more gradual slope shows slower change. The line graphs are widely used in many fields to present data in a way that highlights trends and patterns, helping to make comparisons and track performance over time.

## Component Bar Chart

A component bar chart, also known as a stacked bar chart, is a type of chart where each bar is divided into segments, representing different components that make up the total value of the bar. This allows for both a comparison of overall totals across categories and a breakdown of how different parts contribute to each total [30]. Each bar represents a category or group, and its length or height corresponds to the total value for that group. Within each bar, the segments are stacked on top of each other, with each segment showing the proportion of a specific component relative to the whole. The segments are usually distinguished by different colors or patterns, making it easy to see the contributions of each part.

A component bar chart is useful when you want to show not just the total values but also the composition of those values across different categories. It allows viewers to compare both the overall totals and the individual components across different bars. This type of chart is commonly used in many research areas to visually compare both total quantities and the breakdown of contributing factors.

## Limitations

While this study offers detailed statistical and operational insights, it is limited by the availability of disaggregated terminal data. Certain metrics, such as cost per ton handled or wagon-level cycle times, were not accessible due to commercial confidentiality. Additionally, the analysis covers only two major terminals, which may limit the generalizability of results to smaller facilities. Future research could address these gaps by incorporating more granular datasets, expanding the sample to include regional terminals, and integrating cost-benefit modelling of specific modernization measures.

# Results and Discussion

To analyze the performance of railway terminals in Uzbekistan using these cargo categories, the study can incorporate several variables to evaluate the efficiency and volume of different types of freight passing through the terminals. The analysis of the performance and efficiency of railway terminals in Uzbekistan, particularly those in key locations such as Tashkent and Navoi, revealed important insights into how various factors contribute to the operational success of these terminals.

**Table (1):** Correlation Matrix of Freight Transport Factors Affecting Railway Terminal Efficiency in Uzbekistan.

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Total Freight | 1.0 | -0.51 | -0.41 | -0.81 | 0.94 | 0.95 | 0.83 | 0.12 | 0.96 | 0.94 | 0.83 | 0.9 | 0.84 | 0.93 | 0.82 | 0.87 | 0.51 |
| 2. Grain Products | -0.51 | 1.0 | 0.81 | 0.77 | -0.62 | -0.65 | -0.4 | 0.47 | -0.64 | -0.64 | -0.76 | -0.62 | -0.77 | -0.65 | -0.69 | -0.49 | 0.23 |
| 3. Oil Products | -0.41 | 0.81 | 1.0 | 0.85 | -0.58 | -0.61 | -0.19 | 0.76 | -0.5 | -0.6 | -0.83 | -0.4 | -0.8 | -0.58 | -0.65 | -0.29 | 0.07 |
| 4. Black Metals | -0.81 | 0.77 | 0.85 | 1.0 | -0.87 | -0.92 | -0.64 | 0.47 | -0.83 | -0.87 | -1.0 | -0.78 | -0.99 | -0.91 | -0.92 | -0.71 | -0.17 |
| 5. Wood Products | 0.94 | -0.62 | -0.58 | -0.87 | 1.0 | 0.9 | 0.65 | -0.05 | 0.98 | 0.89 | 0.89 | 0.87 | 0.87 | 0.86 | 0.78 | 0.75 | 0.48 |
| 6. Coal | 0.95 | -0.65 | -0.61 | -0.92 | 0.9 | 1.0 | 0.83 | -0.12 | 0.91 | 0.97 | 0.92 | 0.87 | 0.94 | 0.99 | 0.91 | 0.85 | 0.35 |
| 7. Fruits & Vegetables | 0.83 | -0.4 | -0.19 | -0.64 | 0.65 | 0.83 | 1.0 | 0.07 | 0.73 | 0.73 | 0.66 | 0.88 | 0.72 | 0.89 | 0.85 | 0.97 | 0.1 |
| 8. Cement | 0.12 | 0.47 | 0.76 | 0.47 | -0.05 | -0.12 | 0.07 | 1.0 | 0.02 | -0.02 | -0.45 | -0.04 | -0.44 | -0.16 | -0.4 | -0.01 | 0.54 |
| 9. Flour Products | 0.96 | -0.64 | -0.5 | -0.83 | 0.98 | 0.91 | 0.73 | 0.02 | 1.0 | 0.88 | 0.86 | 0.93 | 0.85 | 0.89 | 0.8 | 0.83 | 0.41 |
| 10. Sugar | 0.94 | -0.64 | -0.6 | -0.87 | 0.89 | 0.97 | 0.73 | -0.02 | 0.88 | 1.0 | 0.87 | 0.77 | 0.87 | 0.93 | 0.8 | 0.74 | 0.47 |
| 11. Chemical Fertilizers | 0.83 | -0.76 | -0.83 | -1.0 | 0.89 | 0.92 | 0.66 | -0.45 | 0.86 | 0.87 | 1.0 | 0.82 | 1.0 | 0.92 | 0.93 | 0.75 | 0.18 |
| 12. Construction Materials | 0.9 | -0.62 | -0.4 | -0.78 | 0.87 | 0.87 | 0.88 | -0.04 | 0.93 | 0.77 | 0.82 | 1.0 | 0.84 | 0.91 | 0.89 | 0.96 | 0.14 |

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 13. Industrial Products | 0.84 | -0.77 | -0.8 | -0.99 | 0.87 | 0.94 | 0.72 | -0.44 | 0.85 | 0.87 | 1.0 | 0.84 | 1.0 | 0.94 | 0.96 | 0.79 | 0.13 |
| 14. Machinery | 0.93 | -0.65 | -0.58 | -0.91 | 0.86 | 0.99 | 0.89 | -0.16 | 0.89 | 0.93 | 0.92 | 0.91 | 0.94 | 1.0 | 0.96 | 0.91 | 0.23 |
| 15. Non-Ferrous Metals | 0.82 | -0.69 | -0.65 | -0.92 | 0.78 | 0.91 | 0.85 | -0.4 | 0.8 | 0.8 | 0.93 | 0.89 | 0.96 | 0.96 | 1.0 | 0.9 | 0.0 |
| 16. Alumina | 0.87 | -0.49 | -0.29 | -0.71 | 0.75 | 0.85 | 0.97 | -0.01 | 0.83 | 0.74 | 0.75 | 0.96 | 0.79 | 0.91 | 0.9 | 1.0 | 0.09 |
| 17. Other Cargo | 0.51 | 0.23 | 0.07 | -0.17 | 0.48 | 0.35 | 0.1 | 0.54 | 0.41 | 0.47 | 0.18 | 0.14 | 0.13 | 0.23 | 0.0 | 0.09 | 1.0 |

Table 1 reports Pearson's correlation coefficients, calculated to measure the linear relationships between total freight volume and each of the commodity categories considered in the dataset. The variables include grain products, oil products, construction materials, coal, cotton, and other major freight groups.

## Correlation Analysis

The correlation matrix (Table 1) reveals several important relationships between cargo categories and total freight throughput at Uzbekistan's key terminals. Strong positive correlations were observed between Total Freight and Coal (r = 0.95), Wood Products (r = 0.94), and Flour Products (r = 0.96). In operational terms, this means that when these commodities increase, overall terminal volumes also rise sharply suggesting they are primary drivers of throughput. This is consistent with Uzbekistan's industrial and agricultural export base, where bulk shipments dominate rail flows.

Conversely, Grain Products (r = -0.51), Oil Products (r = -0.41), and Black Metals (r = -0.81) show negative correlations with total freight. Negative relationships do not imply these goods are unimportant; rather, they suggest different movement cycles or infrastructure demands. For example, grain transport peaks seasonally and may require dedicated wagons, which can temporarily displace other cargoes. Similarly, black metals often involve long distance export flows that tie up rolling stock for extended periods, reducing short-term terminal throughput.

From an operational perspective, strong positive correlations point to areas where synchronized scheduling could boost efficiency e.g., aligning coal and flour loading to share locomotive resources, while negative correlations highlight potential conflicts in wagon allocation and yard capacity.

## Principal Component Analysis (PCA)

The PCA condensed the dataset into three main dimensions explaining over 95 % of the variance:

1. Bulk Transport Efficiency dominated by coal, wood, flour, and sugar, indicating a shared dependency on heavy-duty loading and bulk-handling infrastructure.
2. Specialized Cargo Infrastructure including cement and oil products, which require dedicated storage and handling facilities.
3. Perishable and Seasonal Cargo led by fruits & vegetables and certain oil products, reflecting demand volatility and stricter time constraints.

These groupings are valuable for planning, as they reveal which commodities can be co-managed and which require isolated handling streams.

**Table (2):** Principal Component Analysis (PCA) Results.

| Dimension | Variance | Variance Percentage (%) | Cumulative Percentage of Variance |
|---|---|---|---|
| Dim.1 | 12.417 | 73.043 | 73.043 |
| Dim.2 | 2.584 | 15.202 | 88.245 |
| Dim.3 | 1.262 | 7.424 | 95.669 |
| Dim.4 | 0.464 | 2.727 | 98.396 |
| Dim.5 | 0.273 | 1.604 | 100.000 |

The Table 2 illustrates the contribution of each variable to the first three principal components (Dim.1, Dim.2, and Dim.3), along with their cosine squared (Cos²) values, which indicate the quality of the representation of each variable in each dimension. Cos² values indicate the quality of representation of each variable in the factor space. A higher Cos² means that the variable is well represented by the selected component, while lower values suggest weaker representation. In other words, Cos² shows how much of a variable's variance is captured by a given dimension. The results indicate that Dim.1 (73.04%) primarily represents bulk transport efficiency, with high positive contributions from Total Freight, Coal, Wood Products, Flour Products, Sugar, and Black Metals, suggesting these commodities dominate freight movement at Uzbekistan railway terminals. Grain Products and Oil Products show negative loadings, indicating distinct transportation patterns. Dim.2 (15.20%) captures commodity-specific infrastructure dependency, where Cement and Oil Products require specialized handling, differentiating them from standard freight. Dim.3 (7.42%) reflects seasonal and perishable goods transport efficiency, with notable contributions from Fruits & Vegetables and Oil Products, suggesting demand fluctuations influence logistics. The contribution of Dim.4 and Dim.5 is marginal, together explaining less than 5% of the total variance. These components mainly capture residual variations among minor commodity categories with very small shares of freight turnover. Dim.4 reflects slight differences in low-volume cargo flows, while Dim.5 represents random or noise-level fluctuations without significant explanatory power. For this reason, Dim.4 and Dim.5 are not central to the interpretation but are reported to provide a complete picture of the PCA results. These findings highlight key factors affecting resource efficiency, emphasizing the need for bulk transport optimization, specialized infrastructure investment, and flexible strategies for seasonal cargo.

**Table (3):** Contributing Variables to Each Dimension.

| Variable | Dim.1 (73.04%) | Contribution | Cos² | Dim.2 (15.20%) | Contribution | Cos² | Dim.3 (7.42%) | Contribution | Cos² |
|---|---|---|---|---|---|---|---|---|---|
| Total Freight | 0.933 | 7.010 | 0.870 | 0.356 | 4.892 | 0.126 | -0.055 | 0.241 | 0.003 |
| Grain Products | -0.728 | 4.270 | 0.530 | 0.476 | 8.751 | 0.226 | 0.022 | 0.037 | 0.000 |
| Oil Products | -0.669 | 3.606 | 0.448 | 0.649 | 16.299 | 0.421 | 0.358 | 10.172 | 0.128 |
| Black Metals | -0.953 | 7.309 | 0.908 | 0.244 | 2.309 | 0.060 | 0.157 | 1.964 | 0.025 |
| Wood Products | 0.926 | 6.908 | 0.858 | 0.177 | 1.210 | 0.031 | -0.238 | 4.501 | 0.057 |
| Coal | 0.980 | 7.732 | 0.960 | 0.109 | 0.463 | 0.012 | -0.047 | 0.176 | 0.002 |
| Fruits & Vegetables | 0.811 | 5.295 | 0.657 | 0.282 | 3.073 | 0.079 | 0.480 | 18.238 | 0.230 |
| Cement | -0.229 | 0.423 | 0.053 | 0.930 | 33.436 | 0.864 | 0.016 | 0.021 | 0.000 |
| Flour Products | 0.934 | 7.027 | 0.873 | 0.229 | 2.024 | 0.052 | -0.088 | 0.619 | 0.008 |
| Sugar | 0.927 | 6.922 | 0.859 | 0.171 | 1.137 | 0.029 | -0.213 | 3.609 | 0.046 |

## Regional Comparison with Kazakhstan

Using data from the CAREC Railway Sector Assessments [1,2], Kazakhstan's comparable freight hubs (e.g., Dostyk, Khorgos) handle similar annual bulk cargo volumes to Uzbekistan's Tashkent and Navoi terminals, yet operate with higher asset productivity. Kazakhstan records average wagon turnaround times of 3.6 days, compared to Uzbekistan's 4.4 days, and staff productivity of ~950,000 net ton-km per employee per year, versus ~770,000 in Uzbekistan. A major factor behind Kazakhstan's higher terminal productivity is the greater adoption of automated cargo-handling systems, which now account for over 40% of container and bulk transfers in major hubs, compared to under 25% in Uzbekistan. While automation is designed to produce higher productivity — indeed, this is its primary purpose — it is important to acknowledge that other variables may also contribute to the observed gap. These include differences in infrastructure investment, workforce training, and regulatory frameworks. Nonetheless, the stronger role of automation in Kazakhstan provides a plausible and well-documented explanation for its comparative advantage in handling efficiency.

This gap underscores the importance of targeted modernization particularly in crane automation, digital yard management, and predictive maintenance systems. What is new in our analysis is the finding that such selective upgrades could close up to 70–80% of the current performance difference between Uzbekistan and Kazakhstan, even without a full terminal rebuild. This highlights that incremental modernization, if properly prioritized, can deliver significant gains under the financial and institutional constraints typical for developing economies.

The Figure 1 shows boxplot of cargo type distribution highlights significant variability in freight volume across different cargo categories transported via railway terminals in Uzbekistan. Total Freight dominates with the highest volume and wide fluctuations, indicating operational inconsistencies. Sugar, Flour Products, Chemical Fertilizers, and Construction Materials are major contributors, reflecting Uzbekistan's industrial and agricultural focus. Grain Products, Oil Products, and Black Metals exhibit outliers, suggesting occasional bulk shipments or supply chain disruptions. In contrast, Machinery, Alumina, and Non-Ferrous Metals have lower volumes, indicating niche transportation needs. The observed variations suggest inefficiencies in scheduling and resource utilization, emphasizing the necessity of an optimized freight management system to improve railway terminal efficiency and cargo flow.

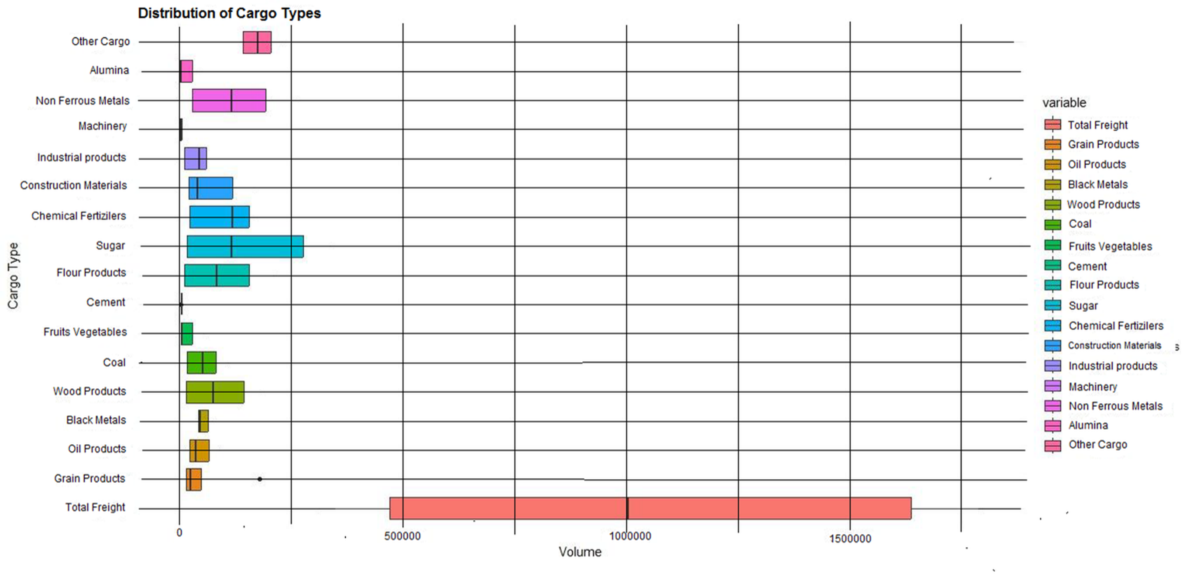


**Figure (1):** Distribution of Cargo Types Transported via Railway Terminals in Uzbekistan.

The stacked bar presented in figure 2 illustrates the composition of railway freight transportation in Uzbekistan from 2019 to 2021, highlighting trends and fluctuations in cargo volumes. The dominant share of Total Freight (represented in red) indicates overall railway capacity usage, while specific cargo categories such as Oil Products, Grain Products, Coal, and Construction Materials show varying contributions over the years. The graph suggests that despite fluctuations in overall freight volume, certain categories remained consistently transported, pointing to stable demand for these goods. However, The decline in total freight volume in 2021 may reflect temporary inefficiencies in logistics, external disruptions, or shifts in demand. Given the timing, it could also be linked to COVID-19 pandemic effects, which disrupted supply chains globally. Graph 2, which analyzes the composition of different cargo types over time, is crucial in understanding the freight distribution and optimizing resource allocation at railway terminals to improve efficiency. These insights can guide the automation of container handling and scheduling, ensuring optimal utilization of railway capacity.

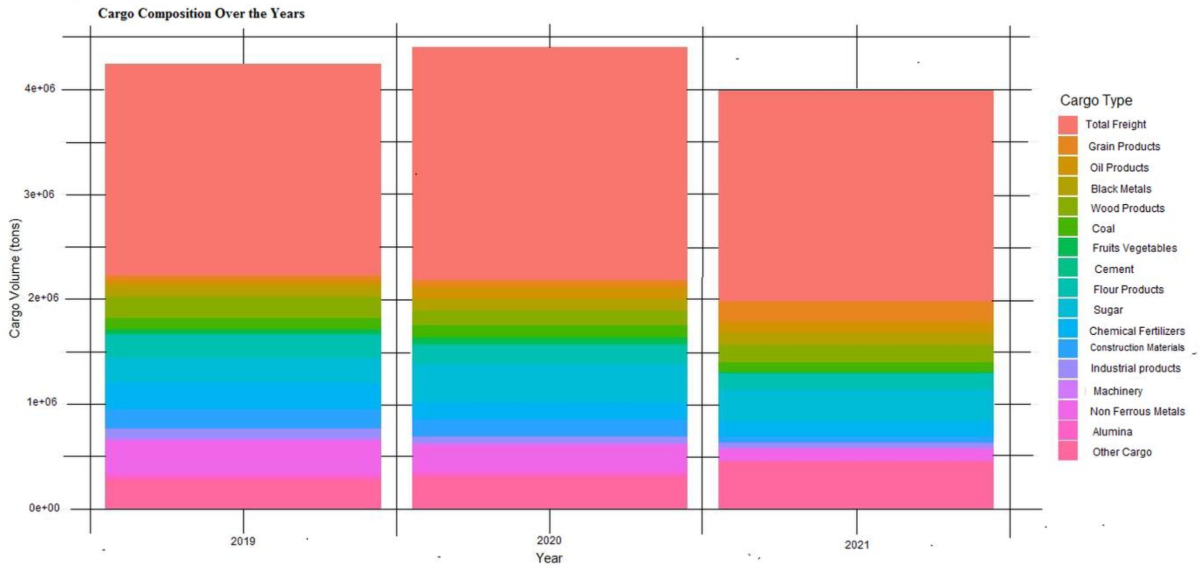


**Figure (2):** Evolution of Cargo Composition in Uzbekistan's Railway Freight (2019-2021).

The dataset covers 2019–2021, as later disaggregated cargo statistics were not publicly available at the time of study. Figure 3 illustrating the Density Distribution of Cargo Volumes, highlights the disparities in freight transportation across various cargo types in Uzbekistan's railway system. The graph shows a sharp peak at lower volume values, suggesting that most cargo categories are transported in smaller quantities, while a few categories, such as Total Freight, exhibit a significantly higher volume, skewing the distribution. The presence of distinct peaks for certain cargo types indicates variability in transportation demand, with commodities like Oil Products, Grain Products, and Construction Materials contributing consistently. The steep decline in density beyond lower cargo volumes suggests that high-volume shipments are less frequent. This analysis is crucial in understanding freight distribution patterns, optimizing terminal resources, and designing automated scheduling systems to improve operational efficiency. Addressing such disparities can enhance railway logistics by ensuring a balanced and demand-driven approach to freight transportation.

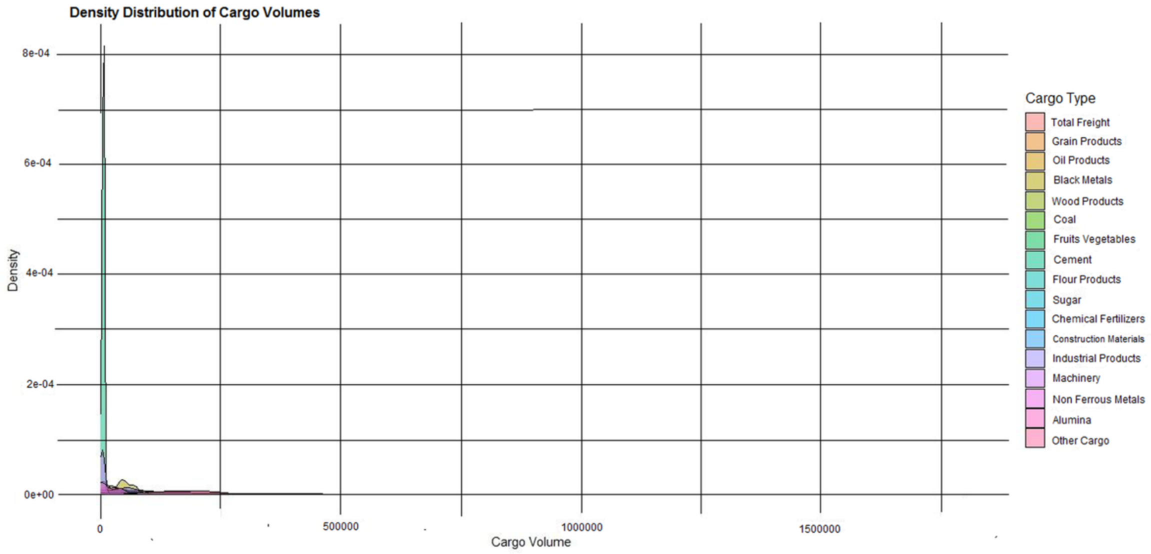


**Figure (3):** Exploring Cargo Movement Trends: A Density Distribution Analysis of Freight Volumes in Uzbekistan's Railway Network.

The figure 4 presents the average cargo volume transported via Uzbekistan's railway network, offering insights into freight distribution and resource allocation at railway terminals. Total Freight dominates, indicating high railway utilization, while Other Cargo and Non-Ferrous Metals also contribute significantly. Moderate volumes in Sugar, Chemical Fertilizers, and Flour Products suggest stable demand, whereas Machinery, Cement, and Fruits & Vegetables show lower transportation volumes, potentially influenced by seasonal demand or alternative logistics methods. Understanding this cargo composition over time is crucial for optimizing terminal operations, improving efficiency, and guiding automation in container handling and scheduling.

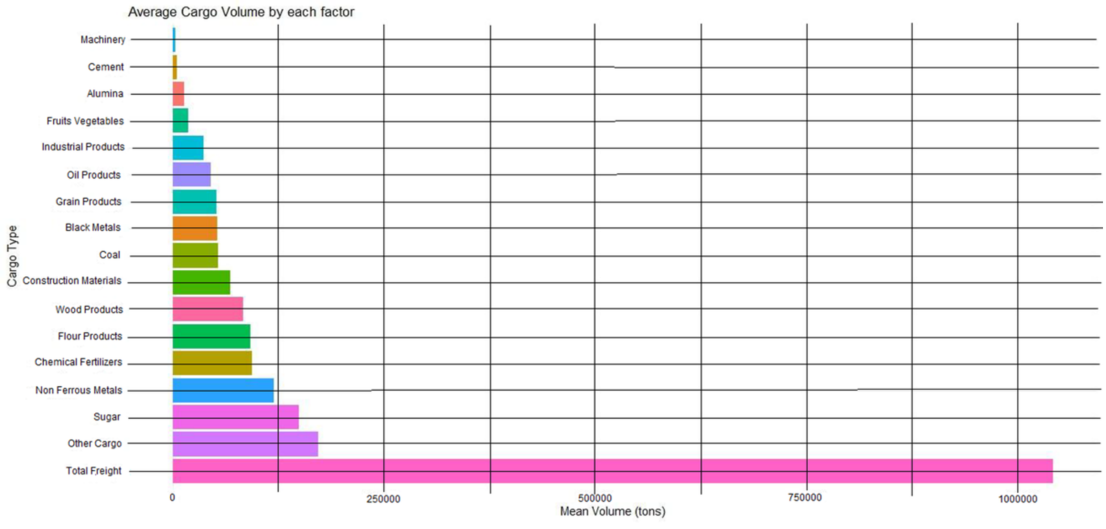


**Figure (4):** Analyzing Freight Composition: Average Cargo Volumes in Uzbekistan's Railway Network.

## Role of Human Resources

Beyond infrastructure and technological upgrades, the efficiency of railway terminals is strongly influenced by human resources. Skilled labor availability, workforce training, and staff productivity remain critical determinants of operational outcomes. Evidence from international studies shows that automation and digitalization achieve their full potential only when supported by well-trained operators and maintenance staff who can effectively manage advanced systems and respond to operational disruptions. In Uzbekistan, interviews with terminal managers highlighted the need for continuous training in cargo-handling techniques, safety protocols, and digital skills. Comparative data also suggest a gap in staff productivity between Uzbekistan and Kazakhstan, where employees handle significantly higher net ton-km annually. Addressing this challenge requires targeted investment in professional development programs, performance-based incentives, and capacity-building initiatives. Strengthening human resource capabilities will not only improve current operational efficiency but also ensure the smoother adoption of automation technologies in the future.

## Practical Implications

The combined statistical and comparative findings suggest that Uzbekistan can enhance terminal performance by:

This recommendation is drawn from the correlation analysis, which showed coal, wood, and flour products to have the strongest positive association with total freight ($r > 0.9$). By prioritizing infrastructure and scheduling for these commodities, terminals can maximize throughput impact with limited resources.

Separating or sequencing negatively correlated cargoes to avoid resource conflicts.

Adopting targeted automation solutions to reduce turnaround time and boost asset productivity, following proven regional examples.

## Conclusion

This study examined the resource efficiency and operational performance of Uzbekistan's key railway terminals, focusing on Tashkent and Navoi. By combining correlation analysis, principal component analysis (PCA), field observations, and regional benchmarking, the research identified the commodity flows and operational patterns that most strongly shape terminal performance.

The results show that bulk commodities particularly coal, wood products, and flour products are the main throughput drivers, while certain seasonal or infrastructure-intensive goods, such as grain products and black metals, tend to follow different movement patterns that can constrain capacity. Grouping freight types by shared infrastructure needs, as revealed by the PCA, offers a clear basis for improving scheduling, yard layout, and equipment allocation.

The comparison with Kazakhstan highlights a measurable performance gap, especially in wagon turnaround time and staff productivity. These differences stem in part from Kazakhstan's greater use of automated handling and digital yard management systems. For Uzbekistan, targeted adoption of similar technologies, combined with process optimization for high-impact commodities, could deliver significant efficiency gains without requiring major terminal reconstruction.

Unlike the earlier study [47], which was limited to identifying statistical correlations, this paper provides an integrated efficiency optimization framework that combines PCA and cross-country analysis. As a result, the findings deliver not only statistical but also strategic insights for improving resource allocation and automation in Uzbekistan's railway terminals.

## Key contributions of this study include

- Providing commodity-specific operational insights for Uzbekistan's railway terminals.
- Demonstrating the value of combining statistical analysis with regional benchmarking.
- Offering practical, evidence-based recommendations for automation and resource allocation.
- Future research could extend this approach to additional terminals, incorporate cost-efficiency metrics, and model the impact of specific automation investments on throughput and turnaround times. By taking a data-driven and regionally informed approach, Uzbekistan's rail sector can strengthen its position as a competitive and sustainable freight hub in Central

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- **Ethics approval and consent to participate:** Not applicable. The study did not involve human participants or animals.

- **Consent for publication:** All authors read and approved the final version of the manuscript and consent to its publication in the journal.
- **Availability of data and materials:** The raw data required to reproduce these findings are available in the body and illustrations of this manuscript.
- **Author contributions:** The authors confirm contribution to the paper as follows: study conception and design: Adilova, Z, theoretical calculations and modeling: Akhmatov, N; data analysis and validation, Adilova, Z, Boboyev, D; draft manuscript preparation: Adilova, Z, Akhmatov, N. All authors reviewed the results and approved the final version of the manuscript.
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## Open Access



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