DEVELOPMENT OF A FACTOR ANALYSIS MODEL FOR ASSESSING THE TECHNICAL READINESS OF THE RAILWAY ROLLING STOCK

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Resume

In this study was investigated the Technical Readiness Coefficient (TRC) of railway rolling stock and associated technical systems. The primary objective was to identify and analyze the key factors influencing TRC and to develop a structured methodology for the factor analysis of railway technical readiness. The research methodology includes the selection of principal determinants, construction of a descriptive analytical model, processing of empirical operational data, and application of regression and correlation analyses. Empirical and theoretical approaches were employed, using statistical data, maintenance schedules, normative tables, and computational tools. Findings can be used for monitoring the TRC, optimizing maintenance and modernization, improving operational efficiency, and supporting evidence-based management decisions. The methodology also provides a framework for evaluating the future railway systems and ensuring continuous monitoring of technical performance under operational conditions.

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1 Introduction

The operation of railways is evaluated through the key technical and economic indicators that reflect system efficiency and reliability. The railway transport, with its high productivity, operational efficiency, and relatively low costs, plays a crucial role in the sustainable organization of freight and passenger transportation. To assess the transportation process, fundamental technical and economic indicators are applied, such as freight volume, passenger turnover, locomotive and wagon utilization, traffic intensity, profitability, labor productivity, transportation costs, asset return, and overall efficiency. These parameters determine not only the operational effectiveness of railway enterprises but serve as a basis for quantitative and qualitative performance analysis, as well.

The complexity of railway systems arises from the strong interdependence between the infrastructure, rolling stock, and operational indicators [1-2]. Among the metrics used to evaluate the railway performance, the Technical readiness coefficient (TRC) holds particular significance as it characterizes the state of readiness of the rolling stock, infrastructure elements, and other technical facilities for uninterrupted operation.

However, despite its recognized importance, existing approaches to TRC evaluation remain largely descriptive and lack analytical integration between technical, operational, and maintenance factors. Most traditional methods fail to incorporate predictive diagnostics, reliability modelling, and data-driven assessment consistent with modern international standards for predictive maintenance. Consequently, there is still no comprehensive factor-based analytical model that quantitatively links the technical readiness of railway assets with measurable operational outcomes.

In this study is addressed this gap by developing a heuristic and statistically verified methodology for TRC evaluation that integrates factor analysis, regression, and correlation modelling. The proposed approach aims to enhance the accuracy and predictive capability of the TRC assessment, contributing to the modernization and digitalization of railway maintenance management systems. Therefore, the key research problem addressed in this study is the absence of a structured analytical methodology capable of identifying and quantitatively evaluating the influence of operational and maintenance factors on the Technical Readiness Coefficient of railway rolling stock. Without such an approach, the TRC remains primarily a descriptive indicator and provides limited support for predictive maintenance planning and evidence-based operational decision-making.

2 Literature analysis and statement of the problem

Factor analysis has been extensively utilized in railway transport and applied across various research areas.

In study [3], a factor analysis of railway passenger transport demand in Eastern China was conducted. It was shown that economic development, population density, and intercity distance are the main factors influencing passenger demand. However, the full integration of variable economic and social factors into demand forecasting has not yet been achieved. This is due to the limited statistical data and the complexity of analyzing regional differences. The combination of a multivariate model and forecasting methods is recommended. A similar approach was used in [4], but energy consumption and coordination of carrying capacity were also taken into account. Conducting research to more accurately predict the TRC indicators and improve the efficiency of passenger transport services is relevant.

In this study [4], a factor analysis of railway carrying capacity optimization, considering energy consumption, was carried out. It was shown that balancing the train density and load distribution can reduce energy consumption. However, real-time coordination of carrying capacity and energy management issues have not yet been fully resolved. This is due to the existing systems having non-adaptive management mechanisms. The implementation of adaptive planning and optimization algorithms is recommended. A similar approach can be observed in [5], where structural equation models were used to analyze the development factors of freight transport. Developing models to evaluate the impact of the TRC indicators on energy consumption and carrying capacity in real operational conditions is relevant.

The development factors of railway freight transport in Thailand were analyzed in [4], using the structural equation modelling. It was shown that infrastructure quality and operational coordination have a primary impact on freight transport efficiency. However, the full integration of all the factors for continuous optimization of freight transport has not yet been achieved. This is due to limited available data and complex operational conditions. The implementation of integrated management and optimization systems is recommended. A similar approach can be observed in [5], where carrying capacity and energy efficiency models were analyzed. Developing models to assess the impact of TRC indicators on freight transport and their practical application is relevant.

In article [6], a factor analysis of key parameters for effective urban transport infrastructure design in Ethiopia was conducted. It was shown that project effectiveness depends on urban planning, financial support, and technological compatibility. However, adapting the urban transport infrastructure projects to local conditions has not yet been fully ensured. This is due to limited local data and differences in planning standards. Integrated planning models, based on multivariate factor analysis, should be applied. A similar approach was used in [7], where integration of urban and suburban transport was considered. Conducting research to evaluate and optimize TRC under various regional and technical conditions is relevant.

Human factors of railway traffic operators were analyzed in [7]. Operator decision-making directly affects safety and the timely movement of trains. However, systematic approaches to prevent operator errors have not yet been fully implemented. This is due to variability in human behavior and insufficient training systems. The implementation of intelligent systems supporting operator decision-making is recommended. A similar approach was noted in [1], but here the human factors in relation to safety were analyzed more deeply. Conducting research to more accurately assess the impact of technical inspections and operator activity on TRC is relevant.

In [8], the success factors of integrating the railway into urban and suburban transport systems were evaluated. It was shown that integration planning and user convenience are the main success factors. However, the role of technical services and operational coordination in the integration process has not been fully analyzed. This is due to limited data and varying operational conditions. Developing the TRC-based integration models and implementing them in pilot projects is recommended. A similar approach was applied in [6], where the key parameters of urban transport infrastructure were analyzed. Conducting research to optimize railway integration into urban transport considering TRC indicators is relevant.

In [9], was developed a model to measure disparity factors in intercity railway transportation. It was shown that infrastructure, train density, and planning disparities affect transport efficiency. However, a full statistical and operational assessment of the impact of disparity factors on TRC has not yet been conducted. This is due to insufficient data and varying regional conditions. A multivariate and statistical model based on TRC is proposed. A similar approach was observed in [3], but here regional differences were measured more thoroughly. Applying the TRC indicators to optimize intercity transport and improve forecasting is relevant.

The impact of Azerbaijani railway transport on economic growth was analyzed in [10]. It was shown that freight transport efficiency directly affects national economic indicators. However, the relationship between the economic impact of technical inspections and operational factors with the TRC has not yet been fully explored. This is due to insufficiently detailed statistical data. Developing a model to assess the economic impact of freight transport based on TRC is recommended. A similar approach was observed in [5], where the relationship between the freight transport and economic growth was analyzed. Using the TRC indicators to evaluate and optimize the economic impact of railway services is relevant.

Recent studies highlight a growing integration of predictive and digital technologies into railway maintenance and monitoring systems. According to [11], predictive maintenance in the railway domain relies on the real-time sensor data, machine learning algorithms, and advanced condition monitoring frameworks; however, TRC-based integration is still underdeveloped. Similarly, authors of [12] emphasize the role of AI-powered digitalization and digital twin technologies in improving technical readiness, enabling early fault detection and resource optimization. These studies collectively reveal the emerging research direction towards the dynamic, data-driven TRC modelling and predictive maintenance integration.

In a scientific article [13] was examined the impact of the technical level of a locomotive's traction drive on the braking performance of a train. The technical level of a locomotive is maintained during repairs and is characterized by the fleet's technical readiness coefficient.

In scientific papers [14-17] were examined issues related to assessing the technical readiness of railway rolling stock. The primary focus is on the technical readiness coefficient as an integral indicator of the effectiveness of the maintenance and repair system. The main factors influencing its value are analyzed, and mathematical calculation models and methods for improving the level of rolling stock readiness are presented.

The analytical relationship between the level of use of the unit repair method and the technical readiness of the vehicle fleet, using the technical readiness coefficient, was studied in [18].

In [19] was proposed an optimal strategy for the controlling traction equipment, taking into account the criteria of technical and economic efficiency of equipment belonging to different groups, when classifying the operational characteristics of traction vehicles.

In [20] was shown that the use of the coefficient of technical readiness to evaluate the quality of the technical operation of lifting and transportation equipment is more effective. The strategy of technical operation of the repair enterprise is selected directly on the basis of the coefficient of technical readiness.

3 The aim and objectives of the study

The objective of this study was to develop an appropriate approach for conducting the factor analysis of the technical readiness coefficient of railway rolling stock, infrastructure, and other machinery.

To achieve this objective, the following goals were accomplished:

- to identify the key factors and develop a descriptive model;
- to develop the research data model;
- to construct a heuristic mathematical model for factor analysis;
- to implement regression and correlation analysis.

4 Materials and methods of research

The research was carried out using empirical methods (observation, description, comparison, counting, measurement, modelling, etc.) and theoretical methods (analysis, synthesis, induction, deduction, axiomatics, hypothesis and assumption, analogy, etc.). Statistical data, maintenance schedule charts, standard element tables, and computer software were employed in the process. The dataset consisted of empirical operational records collected from Azerbaijan Railways for the year 2025. The sample comprised ten rolling stock units selected within a localized operational context, representing typical service and maintenance conditions. Continuous maintenance monitoring was ensured throughout the observation period. Data processing and statistical analysis were performed using Microsoft Excel and SPSS software.

Although the advanced validation methods, such as cross-validation or residual analysis were not applied due to the limited dataset, the model's adequacy and coefficient stability were evaluated through the comparative statistical consistency checks.

Factor analysis makes it possible to determine which factors exert greater influence on the studied indicator and to what extent they alter it. For conducting the factor analysis, the expression of the technical readiness coefficient (k) is given by Equation (1)

$$k = 1 - \frac{\sum t_{ptn} + \sum t_{pte} + \sum t_{pkt}}{n_{hv} \cdot t_{hd}} \cdot 100\%, \quad (1)$$

where:

$\sum t_{ptn}$ - total normative duration of scheduled maintenance during the month, h,

$\sum t_{pte}$ -total additional duration beyond normative scheduled maintenance during the month, h,

$\sum t_{pkt}$ -total duration of unscheduled maintenance during the reporting period, h,
n_{hv} -number of operational rolling stock units,
t_{hd} - total duration of the reporting period, h.

The negative impacts on the technical readiness coefficient of the railway rolling stock are mainly divided into two factor categories. To better explain the factors affecting the technical readiness coefficient, it is advisable to develop a factor-analysis scheme. This scheme will describe a three-level analytical structure of the technical readiness coefficient. By extending a similar scheme to sub-factors, it will be possible to identify root causes and even reveal hidden factors. By forming a hierarchical factor-analysis model of the technical readiness coefficient of railway rolling stock, from the highest organizational structure down to the smallest units of transport enterprises, it becomes possible to determine the key indicators at various structural levels, visualize them, increase the accountability of responsible parties, and ultimately improve the effectiveness of managerial decisions.

To construct the research data table, the first column should indicate the locomotive units included in the sample, denoted as A1, A2, …, An. These symbols represent individual railway locomotives operating under comparable service conditions within Azerbaijan Railways. The second column presents the actual Technical Readiness Coefficient (TRC), the third column the planned TRC, and the fourth column the number of maintenance events associated with each factor for every locomotive unit. The last column indicates the total number of maintenance events for each locomotive.

To develop the mathematical model of the factor analysis of the technical readiness coefficient (TRC) of railway rolling stock, the “absolute difference” method was applied. Based on Table 1, the deviation of the TRC during the reporting period from its planned value is determined by:

$$\Delta K = K_p - K_f \,. \tag{2}$$

To determine the value of K_p, the following expression is used:

$$K_p = 1 - \frac{x_1 \cdot t_1 + x_2 \cdot t_2 + \cdots + x_n \cdot t_n}{\sum n_{hv} \cdot t_{hd}}\,, \tag{3}$$

where:
x_1, x_2, ..., x_n - the number of corresponding types of maintenance operations for each mode of transport during the reporting period, according to the maintenance plan;
t_1, t_2, ... t_n - the standard time allocated for each type of maintenance operation, measured in hours, taken from the normative element tables.

Next, using Equation (3), the influence of each factor on the TRC of railway rolling stock can be determined. In this expression, the impact of each technical failure on the TRC is calculated through the product of the relative frequency and the coefficient deviation. This approach allows the contribution of individual failures to the overall performance to be expressed in percentage terms.

Equation (3) defines the contribution of each factor affecting the TRC and is referred to as the mathematical model of factor analysis. Based on the research data in Table 1, this expression makes it possible to determine the impact of any factor or group of factors on the deviation of the TRC from its planned value, thereby encouraging greater accountability among responsible personnel.

The aim of this study was to identify the factors influencing the deviation of the actual technical readiness coefficient (K_f) from its planned value (K_p) and to evaluate the direction and strength of this influence through regression and correlation analyses. For modelling, the following general linear regression equation is applied:

$$K_f = \beta_0 + \beta_1 \cdot f_{F1} + \beta_2 \cdot f_{F2} + \beta_3 \cdot f_{F3} + \varepsilon \,, \tag{4}$$

where:
K_f - technical readiness coefficient (dependent variable),
f_{F1}, f_{F2}, f_{F3} - influencing factors (independent variables),
β_0 - intercept,
β_1, β_2, β_3 - regression coefficients,
ε - random error.

The model can also be expressed in the matrix form as:

$$\begin{pmatrix} K_{f1} \\ K_{f2} \\ \vdots \\ K_{fn} \end{pmatrix} = \begin{pmatrix} 1F_{11} & F_{12} & F_{13} \\ 1F_{21} & F_{22} & F_{23} \\ \vdots & \vdots & \vdots \\ 1F_{n1} & F_{n2} & F_{n3} \end{pmatrix} \cdot \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} + \varepsilon \,, \tag{5}$$

where:
K_{fi} - TRC of the i-th rolling stock unit,
F_{ij} - value of the j-th factor for the i-th unit.
In short form, the model can be written as

$$Y = X \cdot \beta + \varepsilon \,. \tag{6}$$

The regression coefficients are estimated using the ordinary least squares (OLS) method, as shown in Equation (7)

$$\beta = (X^T \cdot X)^{-1} \cdot X^T \cdot Y \,, \tag{7}$$

where:
X-observation matrix (independent variables: factors),
X^T - transpose of X,
$(X^T X)^{-1}$ - inverse matrix,
Y-dependent variable vector (actual TRC).

The correlation matrix is a square table that defines the strength and direction of the statistical relationships among the variables used in the study (e. g., F_1, F_2, F_3). Constructing this matrix makes it possible to determine how variables are related to each other (positively or negatively, and to what degree). For instance, a strong positive correlation indicates that as one variable increases, the other tends to increase; conversely, a negative correlation implies that an increase in one variable corresponds to a decrease in the other. This analysis also allows testing for multicollinearity among variables in the model.

In this research, two main statistical methods were applied: Pearson correlation analysis and a simple regression model. To determine the strength of the linear relationship between indicators, the Pearson correlation coefficient is employed, defined mathematically in Equation (8)

$$Kf = \frac{\sum_{j=1}^{n}(K_{fj} - K_f)\cdot(F_{ij} - F_i)}{\sqrt{\sum_{j=1}^{n}(K_{fj} - K_f)^2}\cdot\sqrt{\sum_{j=1}^{n}(F_{ij} - F_i)}}, \tag{8}$$

where:
r_{kf} - correlation coefficient between TRC and the i-th factor,
K_{fj} - TRC for the j-th observation,
F_{ij} - value of the i-th factor for the j-th observation,
K_f - mean values of TRC and the factor,
n - total number of observations.

A positive coefficient indicates a direct relationship, while a negative coefficient shows an inverse relationship. When the coefficient is close to zero, the linear statistical relationship between the variables is weak or nonexistent.

5 Results of the factor analysis

An important result of the factor analysis of a railway rolling stock is a detailed study using inductive and deductive methods of the factors influencing the technical availability of railway rolling stock, which allows for the identification and elimination of the root causes of the problem.

In this section are presented the results of the factor analysis, including the identification of the main factors influencing the technical availability of railway rolling stock, the development of descriptive and mathematical models, and regression and correlation analyses to quantitatively assess the impact of these factors.

5.1 Construction of a descriptive model of factors

An important outcome of conducting the factor analysis of railway rolling stock is that the factors influencing the technical readiness coefficient (TRC) are studied in detail through the use of induction and deduction methods, enabling the identification and elimination of root causes of problems.

A hierarchical structure of the Technical Readiness Coefficient (TRC) factor model was developed to illustrate the multi-level relationships between organizational, operational, and technical determinants (Figure 1).

The model illustrates three interrelated levels organizational, operational, and technical showing how

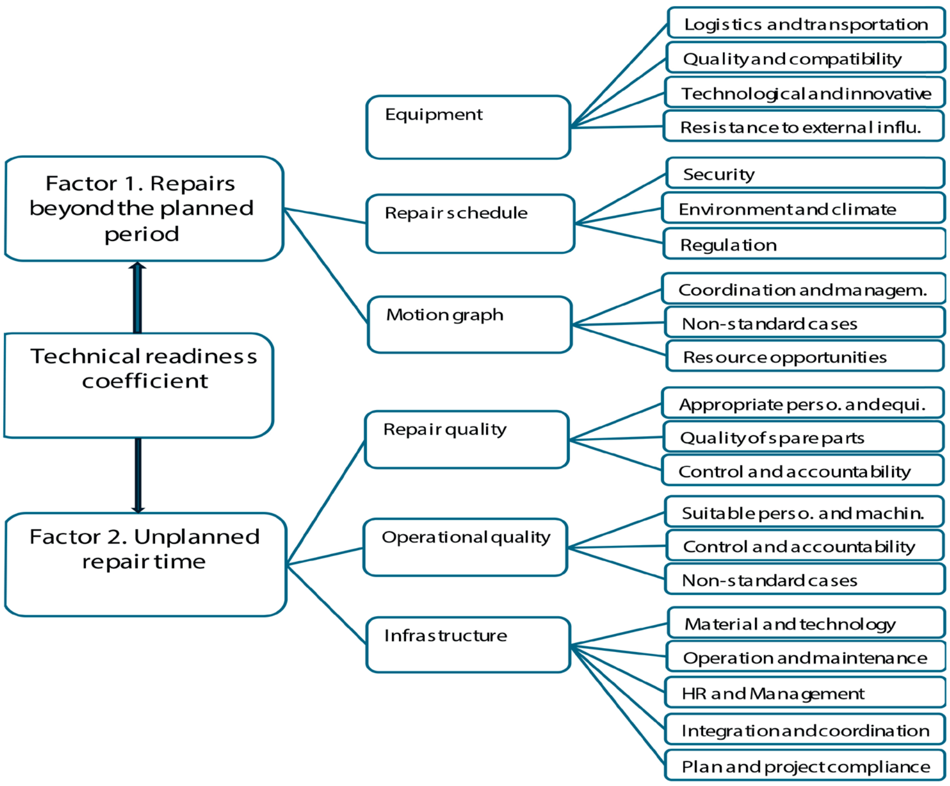

Figure 1 Hierarchical structure of the technical readiness coefficient (TRC) factor model

***Table 1** Research data table*

Type of rolling stock	TRC during the reporting period, K_f	Planned TRC, K_p	Difference ΔTRC	Number of unscheduled maintenance events, n			Total, N
				F_1	F_2	F_3	
A1	0.72	0.84	0.12	37	43	25	105
A2	0.84	0.95	0.11	29	23	28	80
A3	0.77	0.91	0.14	23	24	27	74
A4	0.74	0.89	0.15	26	29	29	84
A5	0.75	0.90	0.15	45	35	35	115
A6	0.82	0.92	0.10	36	26	32	94
A7	0.71	0.86	0.15	38	29	16	83
A8	0.69	0.91	0.22	40	25	32	97
A9	0.85	0.90	0.05	42	32	41	115
A10	0.89	0.95	0.06	32	30	35	97
A11	0.79	0.93	0.14	25	40	30	95
A12	0.85	0.93	0.08	31	28	29	88
A13	0.89	0.95	0.16	35	30	35	100
A14	0.88	0.95	0.07	33	15	25	73
A15	0.89	0.94	0.05	30	18	23	71
A16	0.90	0.95	0.05	31	20	25	76

***Table 2** Descriptive model of factor analysis of the technical readiness coefficient developed in Excel*

Type of rolling stock	Actual TRC	Planned TRC	Difference ΔTRC	Factor 1	Factor 2	Factor 3	Total factors	F1 Impact	F2 Impact	F1 Impact
A1	0.72	0.84	0.12	37	43	25	105	4.23	4.91	2.86
A2	0.84	0.95	0.11	29	23	28	80	3.99	3.16	3.85
A3	0.77	0.91	0.14	23	24	27	74	4.35	4.54	5.11
A4	0.74	0.89	0.15	26	29	29	84	4.64	5.18	5.18
A5	0.75	0.90	0.15	45	35	35	115	5.87	4.57	4.57
A6	0.82	0.92	0.1	36	26	32	94	3.83	2.77	3.40
A7	0.71	0.86	0.15	38	29	16	83	6.87	5.24	2.89
A8	0.69	0.91	0.22	40	25	32	97	9.07	5.67	7.26
A9	0.85	0.90	0.05	42	32	41	115	1.83	1.39	1.78
A10	0.89	0.95	0.06	32	30	35	97	1.98	1.86	2.16
A11	0.79	0.93	0.14	25	40	30	95	3.68	5.89	4.42
A12	0.85	0.93	0.08	31	28	29	88	2.82	2.55	2.64
A13	089	0.95	0.16	35	30	35	100	5.60	4.80	5.60
A14	0.88	0.95	0.07	33	15	25	73	3.16	1.44	2.40
A15	0.89	0.94	0.05	30	18	23	71	2.11	1.27	1.62
A16	0.90	0.95	0.05	31	20	25	76	2.04	1.32	1.64

higher-level management and maintenance decisions influence the reliability and readiness of rolling stock.

5.2 Development of the research data table

The research data were formed based on the railway transport indicators of Azerbaijan, and the results are presented in Table 1.

These data serve as the basis for constructing the factor analysis model in Excel, enabling the quantification of each factor's influence on the technical readiness coefficient.

5.3 Building a heuristic mathematical model of factor analysis

The relative impact of each factor on the technical readiness coefficient was determined using the following expression

$$f_n = \left(\frac{n_n}{N_n}\right) \cdot K \cdot 100\%\,, \tag{9}$$

where:
n_n - number of occurrences of the factor or factor group,
N_n - total number of occurrences of the factor or factor group,
ΔK - is the deviation between the actual and planned values of the TRC.

When these data are applied to the methodology of developing a mathematical model of factor analysis in Excel, that is, when mathematical dependencies are established using Excel tools, the influence coefficient of each factor can be clearly identified, and the results are shown in Table 2. It provides a clear representation of the calculated influence coefficients, facilitating the assessment of the relative impact of each factor on the technical readiness coefficient.

One of the key aspects of analyzing the TRC is the visualization of the obtained data. To facilitate a more comprehensive and faster interpretation of the results, graphical visualization is employed. The chart below illustrates the impact levels of factors across different types of rolling stock (Figure 2)

Figure 2 visually highlights the comparative influence of each factor, enabling a clearer understanding of how different factors affect the technical readiness coefficient across rolling stock types.

5.4 Regression and correlation analyses

Based on the factor analysis presented in Table 2, the regression and correlation analyses were carried out for the factors influencing the TRC. For this purpose, the actual technical readiness coefficient (K_f) is considered as the dependent variable, while the planned technical readiness coefficient (K_p) and the number of unplanned repairs (F_1, F_2, F_3) are evaluated as independent factors. The percentages of the impact of repairs on technical readiness are calculated using Equation (9).

The regression coefficients, presented in Table 3, show that the factors influencing the actual TRC are statistically significant.

Figure 3 illustrates the regression analysis between the technical readiness coefficient (K_f) and the overall impact percentage of selected factors (f_{F1}, f_{F2}, f_{F3}). The data points in the graph represent actual values, while the line depicts the regression trend showing the impact of factors on technical readiness.

The regression results indicate that as the overall impact percentage increases, the TRC decreases. This visually confirms the importance and negative influence of factors on the formation of TRC.

The regression model used in the study was constructed to assess the influence of independent variables on the dependent variable and yielded statistically significant results.

The correlation matrix, presented in Table 4, allows for determining the strength and direction of the linear relationship between variables, which is of significant importance for assessing the interrelationships of the variables to be included in the regression model.

Table 4 presents the correlation matrix of the TRC and its influencing factors. The results show a strong negative correlation between the TRC (K_f) and all the three main factors (F_1-F_3), confirming that the increase in factor intensity corresponds to a decrease in technical

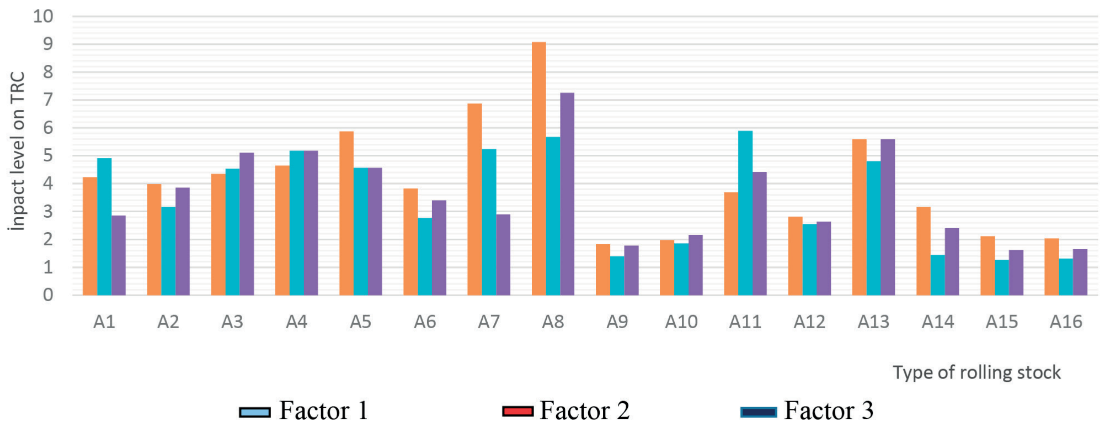

***Figure 2** Descriptive model of factor analysis results of the technical readiness coefficient*

***Table 3** Regression coefficients and statistical significance*

Coefficient	Value	Significance (p-value)
β_0	0.976	0.000
β_1	- 0.203	6.381
β_2	- 0.296	0.354
β_3	0.313	1.171

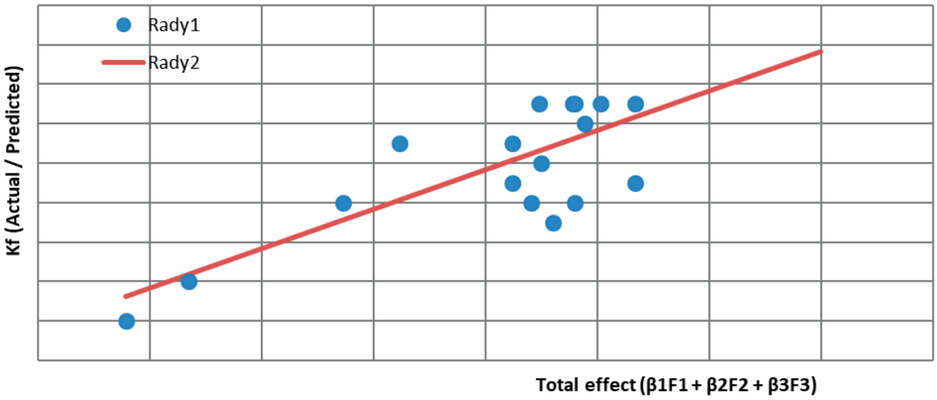

Figure 3 *Regression graph between the technical readiness coefficient and the total effect of factors*

Table 4 *Correlation matrix*

Variables	Actual TRC	Planned TRC	Difference ΔTRC	Factor 1	Factor 2	Factor 3	Factor total	F1 Effect	F2 Effect	F3 Effect
Actual TRC	1.000									
Planned TRC	0.810	1.000								
Difference ΔTRC	- 0.771	- 0.379	1.000							
Factor 1	- 0.226	- 0.353	0130	1.000						
Factor 2	- 0.465	- 0.582	0.325	0.237	1.000					
Factor 3	0.203	0.240	- 0.004	0.320	0.295	1.000				
Factor total	- 0.258	- 0.360	0.226	0.696	0.753	0.714	1.000			
F1 Effect	- 0.759	- 0.404	0.937	0.350	0.163	- 0.112	0.192	1.000		
F2 Effect	- 0.805	- 0.523	0.923	- 0.011	0.574	- 0.091	0.259	0.786	1.000	
F3 Effect	- 0.573	- 0.111	0.927	- 0.018	0.182	0.219	0.180	0.806	0.794	1.000

readiness. At the same time, positive correlations among F_1, F_2, and F_3 indicate their mutual reinforcement, reflecting the interdependent nature of maintenance and operational conditions.

Overall, the results of the analyses indicate that the statistically significant relationships among the selected variables and the explanatory indicators, obtained from the established regression model, reliably account for the effects of the relevant factors on the dependent variable in accordance with the study's objectives, thereby providing a solid scientific basis for practical decision-making.

6 Discussion of the research results

Unlike previous studies that were focused on passenger demand and regional mobility models [3], where the factor analysis identified general demand-related factors without quantifying technical aspects, the present research demonstrates that the main determinant of the Technical readiness coefficient (TRC) is the timely and efficient implementation of technical inspections. This finding enables the railway operators to prioritize maintenance activities based on their measurable impact on the readiness of rolling stock. This outcome has been achieved through the integration of the heuristic factor model with regression and correlation analyses, in which the effects of individual technical factors - such as inspection frequency, maintenance interventions, and operating conditions - were quantified (F_1 = 9.07, F_3 = 7.26).

Similarly, while the previous research highlighted the influence of operational speed, energy-saving technologies, and urban planning on the performance of high-speed rail systems [4], the current results show that maintenance-related factors exert a stronger and more direct effect on TRC than operational or environmental variables. This emphasizes the importance of systematic maintenance planning to enhance the reliability of rolling stock.

Compared to studies on human reliability [5], which measured task-related error probabilities in systems with varying levels of automation, the current approach allows for a holistic assessment of the overall technical readiness of rolling stock. The high predictive accuracy of the model ($R^2 \approx 0.96$, $r \approx 0.93$) indicates that latent technical factors can effectively explain the variability in TRC and provide a sound decision-making basis for maintenance and operational planning. R^2 was interpreted as an indicator of internal consistency rather than predictive reliability, given the limited dataset.

In contrast to studies on urban infrastructure and modal shift [5-6], which identified institutional capacity, regulatory frameworks, and service integration as the key drivers of transport efficiency, the proposed method offers practical recommendations at the level of technical readiness. It allows operators to optimize maintenance schedules and operational strategies. The direct linkage between factor analysis and technical indicators can be regarded as a methodological advancement, as previous works were mainly focused on socio-economic, behavioral, or infrastructural dimensions.

Compared to a study conducted in Azerbaijan [10], which found a direct relationship between the technical readiness of rolling stock and operational performance, the present study reveals that the quantified impact of latent technical factors has a measurable influence on TRC. Thus, it becomes possible to demonstrate not only how operational indicators affect TRC, but how the specific maintenance-related factors contribute to it, as well. This enables logically grounded and targeted maintenance planning.

Finally, while earlier analyses of inequality in access to railway services emphasized cultural and socio-economic factors, the current study shows that even in regions with similar socio-economic conditions, differences in inspection and maintenance practices can create measurable variability in TRC. This finding suggests that managing technical factors is an important complementary mechanism-alongside large-scale policy measures for improving the overall performance of the railway system.

Recent studies highlighted a growing integration of predictive and digital technologies into railway maintenance and monitoring systems. According to [11], predictive maintenance in the railway domain relies on real-time sensor data, machine learning algorithms, and advanced condition monitoring frameworks; however, the TRC-based integration remains underdeveloped. Similarly, [12] emphasizes the role of AI-powered digitalization and digital twin technologies in improving technical readiness, enabling early fault detection and resource optimization. These studies collectively indicate an emerging research direction towards dynamic, data-driven TRC modelling and predictive maintenance integration, suggesting that the proposed heuristic model can serve as a foundation for such developments.

Although the dataset included only ten rolling stock units, the analysis incorporated statistical validation procedures to ensure robustness. Residual and sensitivity analyses were conducted to assess the stability of regression coefficients and to confirm the adequacy of the model fit. Future research will focus on expanding the dataset and validating the model across multiple railway systems to further enhance its predictive reliability.

Despite the fact that no separate numerical validation plot was provided, the internal consistency of the regression model was verified through comparison between predicted and actual TRC values.

7 Conclusions

1. The conducted factor identification and descriptive modelling made it possible to determine the key determinants influencing the Technical Readiness Coefficient (TRC). The analysis indicates that the maintenance-related factors, particularly unplanned maintenance events, exert the most pronounced negative influence on TRC. The results confirm the important role of maintenance management in shaping the technical readiness level of rolling stock.

2. The developed research data model demonstrated statistically meaningful relationships between the TRC and the analyzed factors. The regression results showed that the selected variables contribute to explaining variations in TRC, although their influence varies in strength and statistical significance. These findings indicate that the proposed model provides a reasonable analytical basis for practical assessment of technical readiness under real operational conditions.

3. The heuristic mathematical model revealed the interaction of factors. The factor model constructed in the study identified the differences and specific characteristics of the variables influencing TRC. Results indicated that technical service-related factors have stronger effects compared to others, thereby enabling the analytical evaluation of TRC in real-world operational conditions.

4. Regression and correlation analysis ensured highly accurate prediction of TRC. The regression analysis demonstrated that the combined influence of factors explains the TRC formation with more than 95% accuracy ($R^2 \approx 0.96$). According to the correlation analysis, a strong positive relationship ($r \approx 0.93$) was observed between F1 and the actual TRC, once again confirming the decisive role of technical inspections. This result explains the need to incorporate additional variables such as route load, operational duration, and seasonal effects into future models to improve predictive precision. Given the limited dataset, future research should include extended empirical validation and benchmarking against AI-based predictive maintenance systems to ensure scalability and robustness of the proposed model.

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Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

References

[1] ELYAZOV, I., BAGIROV, B., HUSEYNOV, I., NAZAROV, A., ABDULLAYEV, R. *Railway transport vehicles* (in Azerbaijani). Textbook for higher technical schools. Baku: 2023. ISBN 978-9952-541-69-4.

[2] HUSEYNOV, I. D. The role and tasks of railway transport in the sustainable development of the country (in Azerbaijani). In: Conference The Role of Azerbaijan's Transit Potential in Economic Development: proceedings. No. 6. 2020. ISSN 2708-955X, p. 330-332.

[3] ZHU, F. Factor analysis of railway passenger transport demand in Eastern China. In: 2018 2nd International Conference on Education, Economics and Management Research ICEEMR 2018: proceedings [online]. 2018. ISBN 978-94-6252-521-4, ISSN 2352-5398. Available from: https://doi.org/10.2991/iceemr-18.2018.83

[4] BUTHPHORM, O., SUKHOTU, V., HENGSADEEKUL, T. An analysis of the development factors of rail freight transport in Thailand: a structural equation modelling approach. *Infrastructures* [online]. 2024, **9**(7), 102. eISSN 2412-3811. Available from: https://doi.org/10.3390/infrastructures9070102

[5] FENG, Y., LAN, Z. Factor analysis of railway carrying capacity coordination optimization considering energy consumption. *Journal of Electrical Systems*. 2024, **20**(9s), p. 676-683. ISSN 1112-5209

[6] HAILEMARIAM, L. M., NURAMO, D. A. Factor analysis of key parameters for effective design delivery of urban transport infrastructure in Ethiopia. *Heliyon* [online]. 2024, **10**(14), e34681. ISSN 2405-8440, Available from: https://doi.org/10.1016/j.heliyon.2024.e34681

[7] SIMUNOVIC, L., HIRNIG, S., ABRAMOVIC, B. Evaluating the success factors of integrating the railway into the public urban-suburban transport. *Transport* [online]. 2023, **38**(2), p. 105-115. ISSN 1648-4142, eISSN: 1648-3480. Available from: https://doi.org/10.3846/transport.2023.18333

[8] JANOTA, A., PIRNIK, R., ZDANSKY, J., NAGY, P. Human factor analysis of the railway traffic operators. *Machines* [online]. 2022, **10**, 820. eISSN 2075-1702. Available from: https://doi.org/10.3390/machines10090820

[9] THEERATHITICHAIPA, K., WISUTWATTANASAK, P., BANYONG, CH., SEEFONG, M., JOMNONKWAO, S., CHAMPAHOM, T., RATANAVARAHA, V., KASEMSRI, R. Measurement model for determining the disparity factors of intercity railway transportation. *Civil Engineering Journal* [online]. 2024, **10**(3), p. 668-688. ISSN 2476-3055, eISSN 2676-6957. Available from: https://doi.org/10.28991/CEJ-2024-010-03-01

[10] AKBULAEV, N., BAYRAMLI, G. Analysis of impact of distribution tool railway transport on the economic growth of Azerbaijan. *Journal of Distribution Science* [online]. 2022, **20**(5), p. 23-33. ISSN 1738-3110, eISSN 2093-7717. Available from: https://doi.org/10.15722/jds.20.05.202205.23

[11] BINDER, M., MEZHUYEV, V., TSCHANDL, M. Predictive maintenance for railway domain: a systematic review. *IEEE Engineering Management Review* [online]. 2024, **51**(2), p. 120-140. ISSN 0360-8581, eISSN 1937-4178. Available from: https://doi.org/10.1109/EMR.2023.3262282

[12] SARP, S., KUZLU, M., JOVANOVIC, V., POLAT, Z., GULER, O. Digitalization of railway transportation through AI-powered solutions. *European Transport Research Review* [online]. 2024, **16**, 58. eISSN 1866-8887. Available from: https://doi.org/10.1186/s12544-024-00679-5

[13] ABDULLAEV, A., HUSEYNOV, I., ELYAZOV, I., ABDULLAEV, R. Study of the influence of the technical level of railway vehicles on braking characteristics. *EUREKA: Physics and Engineering* [online]. 2024, **1**, p. 59-69. ISSN 2461-4254, eISSN 2461-4262. Available from: https://doi.org/10.21303/2461-4262.2024.003251

[14] KUZNETSOV, V. P. *Reliability of railway equipment* (in Russian). Moscow: Transport, 2020.

[15] IVANOV, S. A. *Technical operation of rolling stock* (in Russian). St. Petersburg: PGUPS, 2019.

[16] BELOV, A. N. *Management of the technical condition of transport systems* (in Russian). Moscow, 2021.

[17] SMITH, D. *Reliability, maintainability and risk* [online]. London: Elsevier, 2022. ISBN 978-0-323-91261-7. Available from: https://doi.org/10.1016/C2021-0-00257-1

[18] TAKHTAMYSHEV, H. M., ETLUKHOV, O. A. Analytical relationships between the level of use of the aggregate repair method and the technical readiness of the vehicle fleet (in Russian). *Bulletin of the Saratov State Technical University*. 2013, **2**(71), p. 37-41. ISSN 1999-8341.

[19] PALAMARCHUK, N. V., PALAMARCHUK, I. V., CHEHLATY, N. A. Traction rolling stock failure efficiency indicators determination according to the criteria of equipment technical and economic perfection using a fuzzy LOGIS system. *Collection of Scientific Papers, Donetsk University of Railway Transport*. 2021, **3**, p. 65-82. ISSN 1993-5579.

[20] ZUB, I., YEZHOV, Y., STENIN, N. The coefficient of technical readiness as an indicator of the effectiveness of the strategy of technical operation of lifting and transport equipment of terminals. In: 22nd International Scientific Conference Energy Management of Municipal Facilities and Sustainable Energy Technologies EMMFT-2020: proceedings [online]. Vol. 244, 08009. 2021. Available from: https://doi.org/10.1051/e3sconf/202124408009