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Benchmarking road transport sustainability: A composite index approach

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ABSTRACT

Road transport plays a critical role in economic development but remains a major source of energy consumption, greenhouse gas emissions, and road-safety risks. Despite extensive research on sustainable transport, there is still no harmonized, road-specific, cross-country benchmarking tool that allows consistent comparison over multiple years. This study addresses this gap by developing the Composite Road Transport Sustainability Index (CRTSI), a transparent and reproducible framework designed to assess and compare road transport sustainability across 32 countries over the period 2011–2021. The CRTSI is constructed using six indicators reflecting the economic (GDP per capita, freight transport activity), environmental (Road energy consumption, road CO_2 emissions), and social (road traffic fatalities, motorization rate) dimensions of sustainability. This study applies a harmonized and coherent benchmarking configuration that integrates min–max normalization, objective weighting through Principal Component Analysis (PCA) applied to pooled panel data, and linear aggregation into a single composite index, enabling consistent cross-country comparison and multi-year monitoring of road transport sustainability. The robustness of the index is assessed using the Kaiser–Meyer–Olkin (KMO) measure, Bartlett's test of sphericity, and extensive sensitivity analyses based on alternative weighting schemes. The results of the cluster analysis for the year 2021, using the K-means clustering algorithm, reveal substantial cross-country heterogeneity and a clear three-tier sustainability landscape. Nordic countries emerge as frontrunners, driven by low-carbon energy structures, efficient road transport systems, and strong safety performance. In contrast, Germany, Poland, and Turkey rank lower due to energy-intensive freight activity, higher fossil fuel dependence, and elevated road fatality rates, despite otherwise advanced transport systems. Several Southern European countries, including Tunisia, display intermediate and improving trajectories. The CRTSI provides policymakers with a robust decision-support and benchmarking tool, demonstrating that leadership in road transport sustainability is driven primarily by policy choices rather than income levels alone.

1. Introduction

Road transport is a cornerstone of modern economies, enabling passenger mobility, freight circulation, and territorial integration (Ben Abdallah et al., 2013; Regmi, 2024). Nevertheless, it is also a major source of environmental degradation, energy dependence, and road insecurity. The sector remains heavily reliant on fossil fuels and is responsible for substantial greenhouse gas emissions, air pollution, congestion, and noise, generating significant social and economic externalities. According to the International Energy Agency (IEA, 2020), road transport accounts for nearly 35% of global final energy consumption and remains a dominant source of CO_2 emissions, air pollution, congestion, and road traffic fatalities. Recent evidence further highlights the persistent vulnerability of road transport systems to sustainability challenges, including rising motorization rates, urban congestion, and increasing freight demand (OECD, 2022; ITF, 2023). These trends underline the urgent need for reliable and policy-relevant tools to assess and monitor road transport sustainability (Fitschen et al., 2024).

In response to these challenges, the concept of sustainable transport has gained prominence in both academic research and public policy. Sustainable transport systems are expected to satisfy mobility needs while minimizing environmental impacts, improving economic efficiency, and safeguarding social well-being (Black, 2002; Jeon et al.,

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2013). This paradigm is firmly embedded in global and regional policy agendas, including the United Nations 2030 Agenda for Sustainable Development, the European Green Deal, and OECD transport decarbonization strategies, all of which emphasize the decoupling of transport growth from energy consumption, emissions, and safety risks (Soomauroo et al., 2023; Paddeu et al., 2024).

Despite growing consensus on the importance of sustainable transport, its empirical assessment remains methodologically complex (Chakhtoura and Pojani, 2016; Goulart et al., 2023; Ayadi et al., 2024a, b). Sustainability is inherently multidimensional, encompassing economic efficiency, environmental protection, and social well-being (Zheng et al., 2013). The absence of standardized indicators and harmonized evaluation frameworks complicates cross-country and intertemporal comparisons. To address this complexity, composite indicators have been widely adopted as tools for synthesizing multidimensional information into policy-relevant metrics (Haghshenas and Vaziri, 2012; Ben Abdallah et al., 2015). Composite indices rely on normalization, weighting, and aggregation procedures to transform heterogeneous indicators into a single performance measure, thereby facilitating benchmarking and policy evaluation (Illahi and Mir, 2021; Kumar and Anbanandam, 2022). Although these studies have significantly advanced the field, the literature remains fragmented, with substantial heterogeneity in indicator selection, weighting schemes, spatial coverage, and temporal scope.

Sustainability assessment in transport has gained increasing attention (Chatziioannou et al., 2023; Ballantyne et al., 2024; Gruetzmacher et al., 2025). Studies explore environmental impacts, energy efficiency, safety, and modal shifts (Smith et al., 2023; Zhao and Li, 2024). Composite indicators summarize multidimensional data , but most focus on overall transport rather than isolating road transport. Road-transport-specific studies often use national or single-year data, limiting comparability and policy relevance (Kumar and Anbanandam, 2022; Andersson and Pettersson, 2024).

A substantial body of literature has proposed transport sustainability indices at different spatial scales. Foundational contributions by Black (2002) and Castillo and Pitfield (2010) established early conceptual and methodological frameworks, while subsequent studies incorporated advanced statistical techniques and broader indicator sets (Jeon et al., 2013; Haghshenas and Vaziri, 2012). More recent research has refined these approaches by focusing on specific transport modes, regions, or sustainability dimensions (Ayadi et al., 2021; Illahi and Mir, 2021; Zhou et al., 2007). However, methodological heterogeneity persists, and comparative cross-country benchmarking remains limited, particularly when focusing exclusively on road transport systems over time.

More importantly, existing composite indices predominantly adopt a broad transport-system perspective, aggregating road, rail, air, and maritime modes into a single framework. While informative at an aggregate level, this approach tends to obscure the specific sustainability dynamics of road transport, which remains the dominant mode in terms of energy use, emissions, and accident risks. As a result, current indices often fail to provide actionable insights for road-specific policy interventions, particularly when benchmarking countries over time (Ayadi et al., 2021).

Despite substantial progress, several gaps remain in the literature on road transport sustainability. First, there is no harmonized and standardized framework dedicated exclusively to road transport at the cross-country level, limiting comparability due to data heterogeneity. Second, most studies rely on single-year observations rather than multi-year panel data, reducing temporal depth and the ability to capture long-term sustainability trajectories. Third, methodological transparency and reproducibility remain limited, as many indices depend on expert judgment, partial data availability, or indicators that are not consistently comparable across countries. The novelty of the contribution does not lie in the individual methodological tools employed, such as normalization procedures or Principal Component Analysis (PCA), which are well established. Rather, it resides in the unique configuration, selection, and combination of road-transport-specific indicators.

This study addresses these gaps by developing the Composite Road Transport Sustainability Index (CRTSI), a transparent and reproducible benchmarking framework based on harmonized data for 32 countries over the period 2011–2021. The CRTSI focuses exclusively on road transport and integrates six indicators representing the three pillars of sustainability: economic (GDP per capita, freight transport activity), environmental (energy consumption, CO_2 emissions), and social (road traffic fatalities, motorization rate). The methodology relies on well-established normalization and statistical weighting procedures, with extensive robustness checks to ensure reliability and comparability. The index is validated through robustness checks and benchmarked against relevant SDG and ITF indicators, enhancing its practical relevance for policy and cross-country comparisons.

Accordingly, this study seeks to answer the following research questions:

RQ1: How can the multidimensional concept of road transport sustainability be synthesized into a single, objective, and comparable metric across countries?
RQ2: What structural patterns and temporal trends characterize road transport sustainability across countries over the 2011–2021 period?
RQ3: Which policy and structural factors explain the observed heterogeneity between high- and low-performing countries?

The study pursues three interconnected objectives. First, it aims to develop a transparent, harmonized, and road-specific composite sustainability index, leveraging rigorous normalization, PCA-based weighting, and systematic aggregation to capture the multifaceted nature of road transport sustainability. Second, it seeks to benchmark sustainability performance across countries and over time, revealing frontrunners, laggards, and underlying structural patterns that shape the sector. Finally, the study aspires to generate actionable, policy-relevant insights, guiding national and regional strategies toward more sustainable and resilient road mobility.

This study contributes to the literature in three main ways. The theoretical contribution of this study lies in validating the relevance of a road-specific sustainability index structure, demonstrating that isolating road transport yields clearer and more interpretable sustainability patterns than broad, multimodal transport indices. The paper's contribution will now be defined as the development and validation of a focused, road-specific sustainability index for a specific geopolitical context, offering granular, policy-relevant insights that are obscured in broader multi-modal or macro-economic indices. The originality lies in the indicator configuration, the specific policy context it addresses, and the resulting empirical evidence, rather than the statistical techniques themselves.

From a methodological perspective, the study proposes a reproducible framework that combines objective PCA-based weighting with panel data consistency and robustness checks. From a policy perspective, the resulting CRTSI provides a targeted benchmarking tool capable of identifying relative performance, structural weaknesses, and temporal dynamics in national road transport systems.

The remainder of the paper is organized as follows. Section 2 reviews existing approaches to transport sustainability assessment and composite index construction. Section 3 presents the data and methodological framework. Section 4 reports the empirical results and sensitivity analyses. Section 5 discusses the results of the cluster-based analysis and explicitly validates the findings against external and established transport sustainability frameworks. Section 6 outlines the theoretical, practical, and policy implications. Section 7 concludes by highlighting the key contributions, limitations, and directions for future research.

2. Literature review

2.1. Composite indices for transport sustainability assessment

The assessment of road transport sustainability has increasingly relied on the development of composite indices. These indices serve as powerful tools for decision-makers by aggregating multidimensional data, spanning environmental, social, and economic dimensions, into a single, interpretable metric. By synthesizing diverse indicators into a unified measure, composite indices facilitate benchmarking, monitoring, and policy evaluation.

Over the past two decades, a substantial body of literature has proposed and applied such indices using a wide range of normalization, weighting, and aggregation techniques, ranging from simple additive approaches to more advanced statistical methods. Recent developments have also moved toward more granular indicators and the integration of global frameworks, such as the United Nations Sustainable Development Goals (SDGs), to enhance policy relevance and international comparability.

Early macro-level studies laid the methodological foundations of transport sustainability assessment. Black (2002) introduced one of the first composite indices using nine transport indicators and Principal Component Analysis (PCA) to evaluate public transport sustainability across OECD countries and U.S. states. Rassafi and Vaziri (2005) constructed a global transport sustainability index for 79 countries using the Concordance Analysis Technique, while Zhou et al. (2007) proposed a composite energy sustainability index for APEC countries based on Data Envelopment Analysis (DEA). These pioneering studies demonstrated the feasibility of synthesizing transport sustainability into composite metrics but relied on limited indicator sets and cross-sectional data.

Subsequent research expanded both methodological sophistication and spatial scope. Castillo and Pitfield (2010) developed the ELASTIC framework in the United Kingdom using Analytic Hierarchy Process (AHP) weighting, while Yigitcanlar and Dur (2010) proposed the GIS-based SILENT model for urban transport sustainability assessment in Australia. Silva et al. (2010) constructed a composite index for Brazil using 87 indicators weighted through expert judgment. Kolak et al. (2011) and Haghshenas and Vaziri (2012) further advanced cross-country and city-level comparisons, applying AHP and equal weighting approaches to compare transport sustainability across Europe and 100 global cities, respectively.

At the urban scale, numerous studies adopted composite indicators to assess passenger and freight transport sustainability (Zito and Salvo, 2011; Jeon et al., 2013; Reisi et al., 2014; Alonso et al., 2015). These works emphasized the relevance of composite indices for urban planning and policy evaluation but often relied on localized data, expert-based weighting, and single-year observations, limiting cross-country comparability (Sdoukopoulos et al., 2019; Suprayoga et al., 2020).

More recent research has shifted toward hybrid and fuzzy-based models to address uncertainty and complexity in sustainability assessment (Siksnelytė-Butkienė and Streimikiene, 2022). Illahi and Mir (2020, 2021) combined PCA, factor analysis, and fuzzy logic to evaluate transport sustainability in Indian cities, while Ayadi et al. (2021, 2022) extended composite index frameworks by integrating political and territorial dimensions in urban freight transport analysis. Kumar and Anbanandam (2022) and Fulzele and Shankar (2023) applied fuzzy multicriteria decision-making methods to freight transport sustainability, highlighting emerging dimensions such as technology, safety, and efficiency.

Parallel to methodological advancements, growing attention has been paid to road-transport-specific sustainability challenges, particularly decarbonization and freight intensity (Ayadi et al., 2024a,b). Recent studies emphasize the difficulty of decoupling road transport growth from CO_2 emissions, even in advanced economies, and highlight the role of electric vehicle adoption and energy transition policies in reducing road transport energy consumption (Wang et al., 2022). Other contributions focus specifically on road freight sustainability, underscoring its structural importance in national transport emissions (Kumar and Anbanandam, 2022; Fulzele and Shankar, 2023).

At the same time, methodological debates remain active. Li et al. (2023) compare PCA and entropy-based weighting methods, demonstrating that PCA remains a robust and transparent approach when combined with sensitivity analysis. Lee and Yu (2013) explicitly discusses the challenges of constructing composite indices using panel data, reinforcing the importance of methodological transparency and robustness checks when applying PCA to pooled datasets.

Table 1 summarizes key studies that have shaped the landscape of transport sustainability indexing from 2002 to 2025, illustrating the diversity of methodological approaches, indicator sets, and empirical findings. This comparative overview highlights both the significant methodological progress achieved over time and the persistent absence of standardized, road-transport-specific benchmarking frameworks, an important gap that the present study directly addresses.

The longitudinal analysis of the table reveals several critical trends in the field of transport sustainability assessment:

- Evolution of complexity: Early studies (Black, 2002) utilized a limited set of indicators (9), whereas modern frameworks (Velasco and Gerike, 2024) incorporate up to 49 or more, reflecting a more nuanced understanding of urban mobility.
- Methodological sophistication: There is a clear transition from simple equal weighting to objective data-driven methods like Principal Component Analysis (PCA) and Data Envelopment Analysis (DEA), and subjective methods like the Analytic Hierarchy Process (AHP).
- Geographical and sectoral shift: While early research focused on OECD countries, recent literature has shifted towards the Global South (India, Latin America, China), addressing the unique challenges of rapid urbanization and regional inequality.
- Integration of resilience and SDGs: The most recent works (2024-2025) have expanded the definition of sustainability to include climate resilience and explicit alignment with SDG targets, moving beyond traditional environmental metrics to include social dimensions.

2.2. Overview of methodological approaches for composite indicator construction

The construction of composite indicator involves five sequential steps: indicator selection based on sustainability theory and data availability, data collection and sample selection, normalization of indicators, Weighting and aggregation into a single composite score. As shown in Fig. 1, since multiple methods exist for each step, selecting the most appropriate approach is crucial to ensure the reliability and interpretability of the results. Illahi and Mir (2020a,b) reviewed various normalization, weighting, and aggregation techniques applied in transport research worldwide, providing useful guidelines for methodological choice while considering the spatio-temporal context. Building on this, robustness checks, including sensitivity analyses to alternative normalization and weighting methods, are essential to verify the stability of the composite index and to ensure that the final ranking or benchmarking outcomes are not influenced by the methodological choices.

Normalization is a critical step, as the selected indicators are often expressed in different units. Without normalization, disparities in measurement scales could bias the results and allow some indicators to disproportionately influence the composite index. In the literature, several normalization methods are commonly used, including Min–Max, Z-score and distance to the Worst/Best Performance.

According to a comprehensive literature review by Illahi and Mir (2020a,b), which examined 24 studies on the assessment of transport sustainability through composite indices, 44% of researchers applied the Min–Max technique during the normalization phase, followed by 24%

Table 1
Synthetic overview of composite indices in road transport sustainability studies.

Author(s)	Year	Scope/Location	No. of Indicators	Weighting/Aggregation Method	Key Findings
Black	2002	28 OECD countries + US states	9	PCA	Early composite index evaluating public transport sustainability
Rassafi & Vaziri	2005	79 countries	33	Concordance analysis	Strong disparity between developed and developing countries
Zhou et al.	2007	18 APEC countries	3	DEA	Energy efficiency identified as a critical driver of transport sustainability
Yigitcanlar & Dur	2010	Gold Coast, Australia	n.s.	Simple additive aggregation	GIS-based urban transport sustainability index
Castillo & Pitfield	2010	United Kingdom	233	AHP	Developed the ELASTIC framework for comprehensive assessment
Kolak et al.	2011	15 European countries	17	AHP	Cross-country comparison of transport sustainability
Zito & Salvo	2011	36 European cities	24	Equal weighting	Policy-oriented sustainability evaluation
Haghshenas & Vaziri	2012	100 cities worldwide	9	Equal weighting	Developed cities outperform developing ones
Jeon et al.	2013	Atlanta, USA	15	Equal weighting	Multidimensional system performance indices
Alonso et al.	2014	23 European cities	9	Equal weighting	Pillar-based composite sustainability indices
Reisi et al.	2014	Melbourne, Australia	n.s.	Three-step aggregation	Integrated environmental, social, and economic sub-indices
Haghshenas et al.	2015	Isfahan, Iran	9	Composite index	Public transport expansion improves sustainability
Verma et al.	2015	Bangalore, India	16	AHP	Evaluated transport policy impacts
Shaker & Sirodoev	2016	Moldova	n.s.	Multi-indicator scoring	Local sustainable development assessment
Ahangari et al.	2016	28 countries (US + Europe)	10	Equal weighting	National transport sustainability comparison
Mahdoohi & Zarei	2016	Tehran, Iran	n.s.	Network connectivity index	Emphasized public transport development
Dizdaroglu & Yigitcanlar	2016	n.s.	n.s.	Composite index	Transport and local development assessment
Costa et al.	2017	Greater Vitória, Brazil	22	n.s.	Public transport contribution to mobility
Gudmundsson & Regmi	2017	4 Asian cities	10	Equal weighting	Urban transport sustainability evaluation
De Gruyter et al.	2017	26 cities (Asia & Middle East)	15	Quantitative aggregation	Tokyo, Manila, and Chennai top performers
Mahdinia et al.	2018	50 US states + D.C.	89	Algorithm-based composite index	Identified top-performing states
Zope et al.	2019	7 Indian cities + NY & Singapore	n.s.	Equal weighting	Benchmarking of transport sustainability
Illahi & Mir	2020	16 Indian cities	n.s.	PCA/Factor analysis	Five-step urban transport evaluation model
Ayadi et al.	2022	Urban freight transport	n.s.	Extended composite index	Integrated political and territorial dimensions
Wang et al.	2022	China (road sector)	30+	Entropy-based weighting	Significant regional inequality revealed
Velasco & Gerike	2024	Latin American urban public transport	49	Equal weighting	First theory-driven PT index; low performance
Nitwal et al.	2025	Bangalore, India	29	Modified Min–Max, equal weighting	CSTI for metro intervention assessment
Fulton et al.	2025	Low-income countries	n.s.	Benchmarking	Focus on equity and low-carbon transport

Note: n.s. = not specified in the original study.

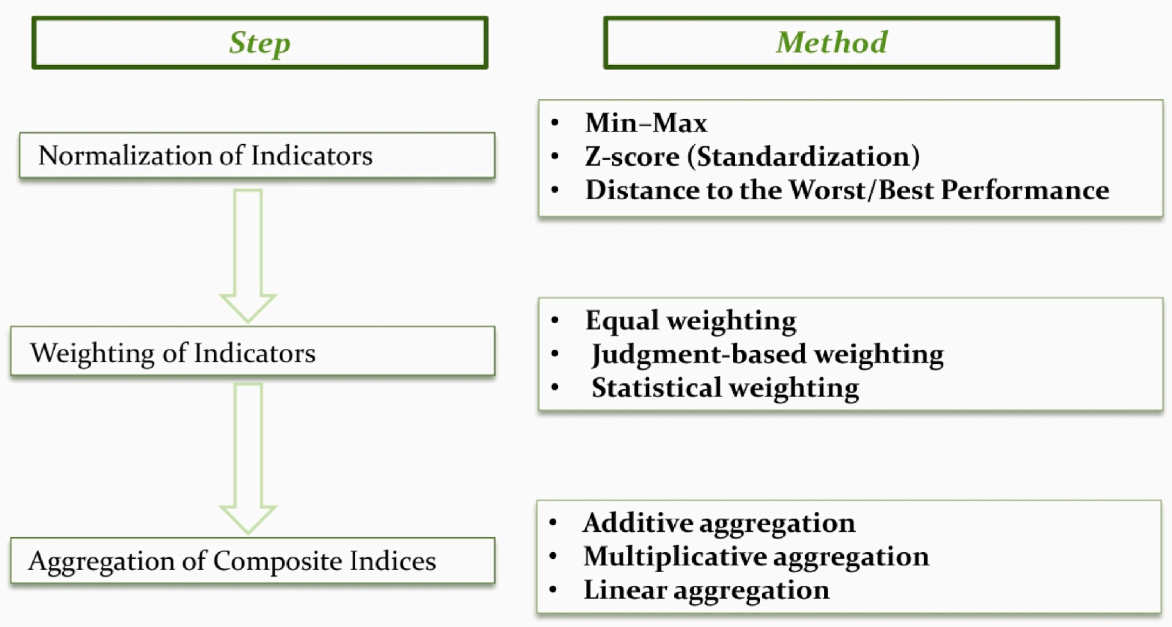


Fig. 1. Process of composite index construction.

who used the Z-score method. To address this, the min–max method was applied, rescaling indicator values between 0 and 1.

Following normalization, the next step involves assigning weights to the normalized indicators. Weighting indicators is a crucial step in the construction of a composite index. It involves assigning a weight to each indicator according to its relative importance in the final index. The assigned weights determine the extent to which each indicator contributes to the composite index, thereby influencing the overall result.

In transport sustainability studies, weighting is an essential stage. The weights attributed to the indicators should reflect the relative importance of the different dimensions for system performance. Several methods exist for determining indicator weights, each suited to different types of analysis and objectives. In this context, three main categories of weighting can be distinguished: equal weighting, judgment-based weighting and statistical weighting. At this stage, Principal Component Analysis (PCA) is applied to reduce data dimensionality while retaining as much original information as possible. PCA is particularly useful when dealing with datasets that include many interdependent variables. This technique assigns weights to each indicator according to its relative importance in the final index. The weights determine the extent to which each indicator contributes to the composite index, thereby influencing the overall result. Indicators that are strongly correlated with the principal components receive higher weights, reflecting their stronger influence on system performance (Black, 2002; Reisi et al., 2014; Mahdinia et al., 2018).

Before proceeding with weighting, it is necessary to ensure that correlations among indicators are not merely the result of redundancy. To verify this, the Kaiser-Meyer-Olkin (KMO) test and the correlation matrix are employed. The KMO test evaluates the adequacy of the sample for factor analysis. A KMO value between 0.6 and 1.0 indicates that the data are well-suited for extraction of latent factors. Conversely, values below 0.5 suggest that factor analysis should be avoided. In essence, the higher the KMO value, the greater the suitability of the dataset for PCA. Once the KMO test and correlation analysis confirm data adequacy, the weighting process can be applied to determine the contribution of each indicator to the composite index.

Aggregation involves combining multiple normalized and weighted indicators into a single value that represents the overall performance or sustainability level. Different aggregation methods reflect different assumptions about the relationships between indicators, such as substitutability or complementarity. They include additive, multiplicative, geometric, and linear aggregation, each with specific characteristics and applications. The choice of aggregation method can significantly influence the final index and the interpretation of results.

2.3. Research gaps and motivation for the CRTSI

Recent studies increasingly rely on composite indicators to assess road transport sustainability by integrating environmental, economic, social, safety, and technological dimensions. Nevertheless, many existing indices remain highly sensitive to weighting schemes and data availability, underscoring the need for transparent and robust aggregation frameworks. The state-of-the-art review confirms that composite indices have become indispensable tools for benchmarking and policy evaluation.

However, as highlighted by Ayadi et al. (2024a,b), significant methodological challenges persist, notably the lack of standardized normalization procedures and the insufficient consideration of the freight transport dimension. Addressing these gaps is essential to achieve a more comprehensive and policy-relevant assessment of road transport sustainability.

Three major research gaps motivate the development of the Composite Road Transport Sustainability Index (CRTSI). First, a modal specificity gap persists. Most existing composite indices adopt a broad, multimodal perspective, aggregating road, rail, air, and maritime transport into a single framework. This approach dilutes road-specific sustainability signals and limits the usefulness of such indices for designing and evaluating road-focused policy interventions, even though road transport remains the dominant contributor to transport-related energy use, emissions, and accident risks.

Second, a panel consistency gap remains unresolved. While several studies provide cross-country comparisons, the majority rely on cross-sectional or short time-span data. Robust multi-year panel indices ensuring strict cross-country and intertemporal comparability, through rigorous control of missing data and indicator consistency, are largely absent from the literature.

Third, a methodological transparency gap persists. Many composite indices rely on expert judgment, ad hoc weighting schemes, or limited robustness testing. Few studies explicitly justify the application of PCA to panel data structures or provide comprehensive sensitivity analyses assessing the stability of results under alternative normalization and weighting schemes.

This study addresses these gaps by proposing the Composite Road Transport Sustainability Index (CRTSI), a transparent, reproducible, and road-transport-specific benchmarking framework constructed from harmonized panel data for 32 countries over the period 2011–2021. The contribution's novelty lies not in the methodological components taken individually, but in their coherent integration into a road-transport-specific, cross-country, and longitudinal framework that enhances both comparability and policy relevance. By combining objective PCA-based weighting with panel consistency and extensive robustness checks, the CRTSI provides a policy-relevant tool capable of identifying relative performance, structural weaknesses, and temporal dynamics in national road transport sustainability.

3. Rationale, study scope and methodological framework of the CRTSI

The methodological rigor of the CRTSI relies heavily on the coherence and justification of the sample, time period, and indicator selection.

3.1. Indicator selection and theoretical justification

Consistent with established sustainable road transport frameworks, which conceptualize sustainability as a multidimensional construct encompassing economic, environmental, social, and safety dimensions, this study selects a parsimonious set of six indicators based on three key criteria: conceptual relevance, frequent use in the transport sustainability literature, and complete data availability over the study period (Black, 2002; Castillo and Pitfield, 2010; Jeon et al., 2013). Rather than exhaustively representing all possible aspects of transport sustainability, the objective is to construct a robust and comparable composite index that captures the core structural dimensions while avoiding redundancy, over-parameterization, and data-driven bias.

The selection of indicators used in this study is firmly grounded in the existing literature, as they represent the most applied measures for assessing transport sustainability. These indicators were carefully chosen to capture the three key dimensions of sustainability, economic, environmental, and social, as illustrated in Fig. 2:

This indicator set is conceptually grouped under the three pillars of sustainability:

Economic and enabling context:

- Road freight transport activity (ton-kilometers per capita) reflects the economic and logistics role of road transport systems, while capturing structural pressure on infrastructure, energy demand, and emissions. It is widely used as a proxy for transport-related economic intensity.
- GDP per capita (constant 2015 USD) is treated as a contextual/enabling factor rather than a direct measure of sustainability performance. It reflects the economic capacity that constrains or enables

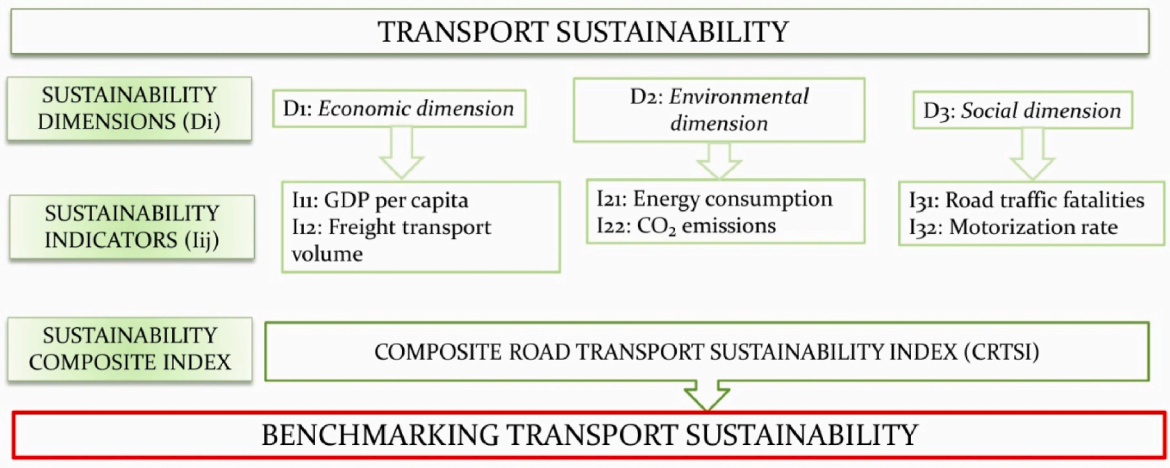


Fig. 2. Transforming sustainability indicators into the CRTSI.

investments in sustainable transport infrastructure, cleaner technologies, and safety improvements.

Environmental dimension:

- Road transport energy consumption (toe per capita) directly captures fuel demand and energy efficiency, reflecting environmental pressure and dependence on fossil fuels.
- Road transport CO_2 emissions (tons per capita) constitute a core climate-related indicator and a direct measure of decarbonization performance. All references to carbon emissions are standardized to CO_2 throughout the manuscript.

Social and safety dimension:

- Road traffic fatalities (per 100,000 inhabitants) represent transport safety and social sustainability, consistently emphasized in international frameworks.
- Motorization rate (vehicles per 1000 inhabitants) reflects accessibility to individual mobility and transport services, while simultaneously capturing potential negative externalities such as congestion and environmental burden.

Together, these six indicators provide a balanced and theoretically coherent representation of road transport sustainability, capturing economic performance, environmental pressure, and social outcomes. By integrating these indicators, the CRTSI offers a comprehensive, policy-relevant, and comparable measure of road transport sustainability, grounded in both theory and data availability.

The novelty of this study does not lie in the individual indicators or statistical techniques employed, which are well established in the literature, but rather in their specific configuration and targeted application. Unlike broad transport sustainability indices that aggregate multiple transport modes, this study focuses exclusively on road transport, acknowledging its dominant contribution to energy consumption, CO_2 emissions, and road safety outcomes. By isolating road transport, the resulting CRTSI provides a more precise and policy-relevant assessment of sustainability performance in this critical sector.

The main contribution of this study is the development of a focused, road-transport-specific composite index (CRTSI) that ensures cross-country and temporal consistency over a decade. While most existing indices adopt a multimodal perspective, the proposed configuration isolates the most dominant and environmentally and socially impactful transport mode road transport through a carefully selected set of six indicators. This targeted focus enables clearer interpretation and more actionable policy insights for road-specific interventions, thereby addressing an important gap in the sustainable transport literature.

3.2. Data collection and sample selection

3.2.1. Data sources

As shown in Table 2, data were collected exclusively from authoritative international sources, namely the World Bank Open Data, Eurostat and the Organisation for Economic Co-operation and Development (OECD). These sources provide standardized definitions, consistent reporting methodologies, and broad international coverage, making them particularly suitable for composite indicator construction.

3.2.2. Justification of country selection for the sample

The selection of the 32 countries included in this study was primarily guided by data consistency, completeness, and cross-country comparability, which are essential for the construction of a robust CRTSI. To preserve the integrity of the panel structure and avoid potential biases associated with data imputation or estimation, only countries with

Table 2
Variables, definitions, units, and data sources.

Variable	Definition	Unit	Source
Road Energy Consumption	Total energy consumed by the road transport sector, reflecting energy efficiency and sustainability.	Thousand tonnes of oil equivalent	Eurostat
Motorization Rate	Number of motorized vehicles per 1000 inhabitants, indicating private vehicle accessibility and transport development level.	Vehicles per 1000 inhabitants	Eurostat
Road Transport CO_2 Emissions	Total CO_2 emitted by the road transport sector, measuring climate impact and environmental pressure.	Tons per capita	OECD
Road Traffic Fatalities	Number of deaths resulting from road accidents or transport-related incidents, reflecting transport safety.	Persons per 100,000 inhabitants	OECD
Freight Transport Volume	Total freight transported by road (tonne-kilometers per capita), reflecting economic activity and transport intensity.	Million tonne-kilometers	OECD
Gross Domestic Product (GDP)	Total value of goods and services produced, reflecting economic performance and its enabling role for transport.	Constant 2015 USD	World Bank

complete and consistent data for all six indicators over the entire observation period were retained. This strict criterion resulted in a final sample of 32 countries.

Such a stringent selection process ensures that the resulting CRTSI is not affected by missing-data treatment and maintains a high degree of temporal and cross-country consistency, thereby providing a reliable basis for robust international benchmarking.

The analysis includes the following countries: Albania, Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Italy, Lithuania, Moldova, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Serbia, Slovenia, Spain, Sweden, Tunisia, Turkey, and the United Kingdom.

Beyond data availability, the selected sample reflects a heterogeneous set of road transport systems and policy contexts, encompassing both advanced and emerging economies, as well as EU and non-EU countries, including neighboring Mediterranean states. This diversity enhances the benchmarking value of the CRTSI by enabling meaningful cross-country comparisons across different levels of economic development, transport demand intensity, infrastructure maturity, and environmental performance. Importantly, the index is designed to assess relative performance rather than absolute sustainability levels, thereby reinforcing its role as a policy-oriented benchmarking tool.

At the same time, the sample is largely composed of OECD and EU member states, which reflects not only data completeness but also the relevance of focusing on an institutionally comparable group of countries. These countries share broadly similar regulatory frameworks, reporting standards, and transport policy objectives, which strengthens the internal consistency and cross-country comparability of the composite index.

3.2.3. Time horizon justification

The analysis covers the period 2011–2021, providing 11 annual observations per country and a total of 352 observations per indicator. This timeframe corresponds to the longest common data availability window for all six indicators across the 32 countries in the major international databases. Selecting this period ensures temporal consistency and cross-country comparability in the construction of the CRTSI.

Limiting the analysis to 2021 is justified by three main considerations. First, data for the subsequent years (2022–2024) were excluded because they lack the necessary harmonization and completeness across all databases, which would have compromised the consistency of the panel and the robustness of the CRTSI. Extending the analysis beyond this year would require data interpolation or imputation, which could compromise the integrity of the composite index.

Second, it is to avoid structural distortions induced by the COVID-19 pandemic, which generated exceptional short-term shocks in key variables, including road transport energy consumption, CO_2 emissions, freight activity, motorization patterns, and road traffic fatalities. The post-2021 period reflects recovery dynamics, emergency policy interventions, and temporary behavioral changes that are not representative of long-term transport sustainability trends and could bias the construction and interpretation of a composite index.

Third, from a structural and policy perspective, the 2011–2021 period captures a decade of significant developments in road transport systems, including rising motorization in emerging economies, increasing freight demand, and the gradual integration of sustainability objectives into national and international transport policies. Moreover, this timeframe aligns with major global policy milestones, notably the lead-up to and early implementation phase of the UN 2030 Agenda for Sustainable Development, making it particularly relevant for evaluating transport sustainability performance in a policy-oriented benchmarking framework.

Overall, this period provides a meaningful, stable, and policy-relevant basis for constructing the Composite Road Transport Sustainability Index, balancing data availability, structural representativeness, and relevance for cross-country comparisons.

3.3. Methodological framework for constructing the CRTSI

The methodological framework for constructing the CRTSI follows a standardized, transparent, and reproducible configuration designed to ensure cross-country and intertemporal comparability. As shown in Fig. 3, the six indicators will be normalized and analyzed using PCA, a statistical technique that reduces data dimensionality while retaining the most relevant information. Applying this methodology to a sample of countries will facilitate the construction of a comprehensive index, enable systematic analysis of the results, and help identify pathways to improve transport sustainability. Subsequently, the normalized indicators will be aggregated to form a composite index representing the overall level of transport sustainability for each country.

3.3.1. Normalization of indicators

To ensure comparability across the six heterogeneous indicators, all variables are normalized to a common scale between 0 and 1. This step eliminates the effect of different measurement units and scales, which is essential for composite index construction. The min–max normalization method is used, as it preserves the relative distribution of the original data and facilitates intuitive interpretation.

The normalized value $I_{i,t}^{\text{norm}}$ for an indicator i at time t is calculated as follows:

$$I_{i,t}^{\text{norm}} = \frac{I_{i,t} - \min(I_i)}{\max(I_i) - \min(I_i)} \tag{1}$$

Where $I_{i,t}$ is the original value of indicator i at time t, and $\min(I_i)$ and $\max(I_i)$ are the minimum and maximum values observed for that indicator across all countries and years.

For indicators where a higher value represents better sustainability (GDP per capita as economic capacity), this formula is applied directly. For indicators where a lower value represents better sustainability (CO_2 emissions, road energy consumption, road traffic fatalities, motorization rate, and freight transport volume), the inverse normalization is applied:

$$I_{i,t}^{\text{norm}} = 1 - \frac{I_{i,t} - \min(I_i)}{\max(I_i) - \min(I_i)} \tag{2}$$

This ensures that, for all indicators, higher normalized values consistently correspond to better sustainability performance, allowing coherent aggregation in subsequent steps. By applying this approach, the CRTSI maintains conceptual consistency across dimensions and enables meaningful cross-country and temporal comparisons of road transport sustainability.

3.3.2. Weighting through Principal Component Analysis (PCA)

To avoid subjective weighting, PCA was employed to derive statistically grounded indicator weights. PCA reduces dimensionality by transforming a set of correlated normalized indicators into uncorrelated Principal Components (PCs), while retaining most of the variance present in the original data. This approach ensures that each indicator's contribution to the CRTSI is determined objectively.

The k-th Principal Component (PC_k) is calculated as a linear combination of the normalized indicators:

$$PC_{k,c,t} = \sum_{i=1}^{N} a_{k,i} \cdot I_{i,c,t}^{\text{norm}} \tag{3}$$

Where $PC_{k,c,t}$ is the score of component k for country c at time t, $I_{i,c,t}^{\text{norm}}$ is the normalized value of indicator i, and $a_{k,i}$ is the factor loading (eigenvector coefficient) of indicator i on component k.

Only components with eigenvalues greater than 1 were retained (Kaiser criterion). The weight ω_k assigned to each retained component k is proportional to the variance it explains relative to the total variance

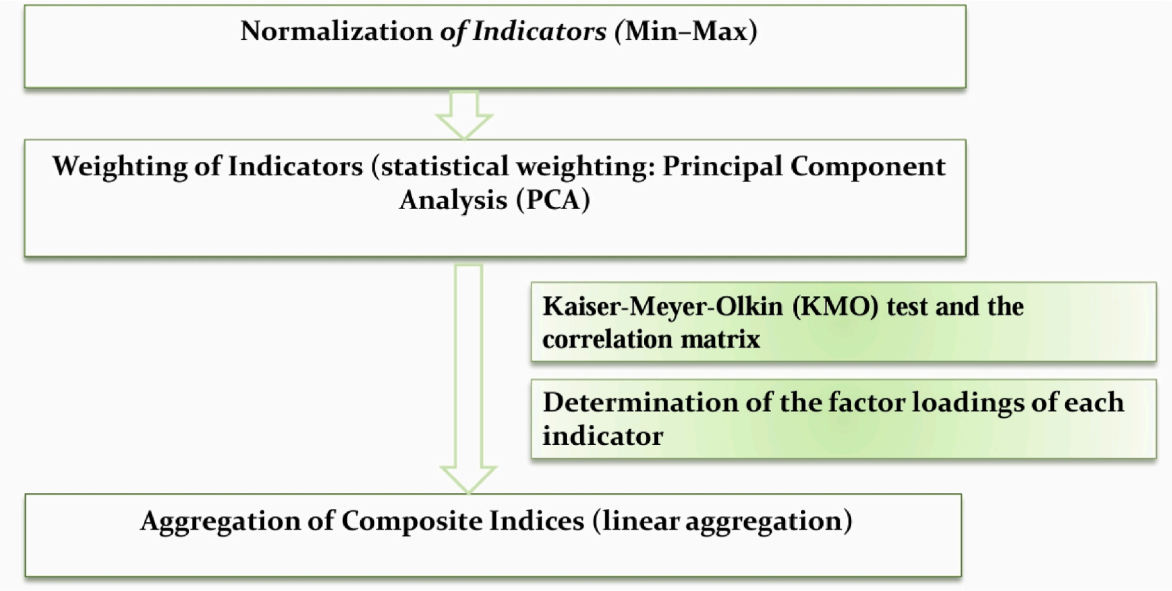


Fig. 3. Framework for selecting composite index methodology.

explained by all retained components (P):

$$\omega_k = \frac{\lambda_k}{\sum_{j=1}^{P} \lambda_j} \tag{4}$$

Where λ_k is the eigenvalue of component k, and P is the number of retained components. Indicator weights are then computed from the normalized component loadings:

$$w_j = \frac{\sum_{k=1}^{m} \lambda_k L_{j,k}}{\sum_{j=1}^{n} \sum_{k=1}^{m} \lambda_k L_{j,k}} \tag{5}$$

Where $L_{j,k}$ denotes the loading of indicator j on component k, m is the number of retained components, and n is the number of indicators.

The dataset used in this study exhibits a balanced panel structure, consisting of observations for 32 countries over an 11-year period, yielding a total of 352 country-year observations. Although PCA is traditionally applied to cross-sectional data, its application to pooled panel data is methodologically sound and widely adopted in the composite indicator literature when the primary objective is structural comparison rather than dynamic analysis.

This choice is justified because the goal is to extract stable structural cross-country relationships among indicators that persist over time, rather than modeling year-specific dynamics. Pooling ensures that the resulting weights reflect average structural patterns across countries and years. The purpose of applying PCA in this context is not to model temporal dynamics within individual countries, but to identify the underlying structural relationships and dominant patterns of cross-country variation in road transport sustainability. By pooling the data, each country-year observation is treated as an independent realization of the same underlying system, enabling the extraction of a common factor structure that is assumed to be stable over the observation period.

This pooled PCA approach ensures that the derived weighting scheme reflects the prevailing spatial heterogeneity and the fundamental interrelationships among the sustainability indicators across countries. As a result, the CRTSI captures relative cross-country performance in a consistent and data-driven manner, while maintaining comparability over time. This methodological choice provides a robust statistical foundation for the construction of the composite index and enhances its suitability as a policy-oriented benchmarking tool.

3.3.3. Aggregation and construction of the CRTSI

The final Composite Road Transport Sustainability Index (CRTSI) for country c at time t is constructed as a linear aggregation of the retained Principal Components, weighted by their respective contribution to the total explained variance (ω_k):

$$\mathrm{CRTSI}_{c,t} = \sum_{k=1}^{P} \omega_k \cdot PC_{k,c,t} \tag{6}$$

Where $PC_{k,c,t}$ is the score of the k-th Principal Component for country c at time t, ω_k is the weight of component k derived from its explained variance, and P is the number of retained components. This approach ensures that indicators contributing more to overall variability in sustainability performance carry greater influence in the composite index.

Alternatively, the CRTSI can also be expressed in terms of weighted normalized indicators:

$$\mathrm{CRTSI}_{c,t} = \sum_{j=1}^{n} w_j \cdot I_{j,c,t}^{\mathrm{norm}} \tag{7}$$

Where w_j is the weight of indicator j derived from the PCA loadings, $I_{j,c,t}^{\mathrm{norm}}$ is the normalized value of indicator j, and n is the total number of indicators.

The CRTSI ranges between 0 (least sustainable) and 1 (most sustainable), enabling straightforward cross-country benchmarking and temporal monitoring of road transport sustainability. This final aggregation synthesizes the theoretical and methodological steps outlined in Equations (1)–(7), including normalization, PCA-based weighting, and factor score calculation, into a policy-relevant, interpretable, and reproducible index.

4. Empirical findings

4.1. Descriptive statistical analysis

Before constructing the CRTSI, it is essential to examine the descriptive statistics of the six selected indicators (Table 3). This allows for an assessment of the distribution, variability, and scale of each variable across the panel of 32 countries over the period 2011–2021. The statistics reported are computed on the pooled panel dataset (N =

Table 3
Descriptive statistics of CRTSI indicators (2011–2021).

Variable	Abbreviation	N	Mean	Std. Dev.	Min	Max
GDP per capita (USD)	GDP	352	27910.00	21240.80	2749.91	103554.00
Motorization rate (vehicles per 1000 population)	MR	352	409.94	163.00	118.00	768.00
Freight transport volume (billion tkm)	FTV	352	67364.80	94926.80	67.00	461582.00
Road energy consumption (Mtoe)	REC	352	9987.79	13611.10	156.45	54584.00
Road transport CO_2 emissions (Mt)	RCO_2	352	94.45	5.96	62.75	100.00
Road traffic fatalities (per 100000 population)	RTF	352	997.61	1334.57	4.00	7530.00

352 observations per indicator), providing a clear overview of the underlying data prior to normalization and PCA-based weighting.

The descriptive statistics of the raw (non-normalized) indicators reveal substantial heterogeneity across countries and over time in all dimensions of road transport sustainability. Economic and activity-related variables, particularly GDP and freight transport volumes, exhibit very large standard deviations and wide ranges, reflecting pronounced differences in economic size, transport demand, and logistics intensity across countries. These scale effects are typical in cross-country panel data and highlight the dominance of large economies in absolute transport activity levels.

Environmental and safety indicators, such as Road Transport CO_2 Emissions and road fatalities, also display considerable dispersion. While CO_2 emissions are relatively concentrated around high values, road fatalities show extreme variability, indicating sharp contrasts in road safety performance across countries. The motorization rate presents marked asymmetry, with a small number of highly motorized countries driving the upper tail of the distribution. This underscores structural differences in mobility patterns, income levels, and transport infrastructure development.

Overall, the strong dispersion, scale heterogeneity, and skewness observed in the raw indicators justify the normalization of variables prior to aggregation and confirm the relevance of a composite index approach. Without normalization, indicators measured on large numerical scales would dominate the analysis, biasing the assessment of road transport sustainability.

To ensure methodological rigor and the suitability of PCA, a series of formal diagnostic tests were conducted on the pooled panel dataset.

4.2. Pre-PCA diagnostics

Prior to the application of PCA, the results reported in Table 4 summarize a set of formal diagnostic tests conducted to assess the degree of multicollinearity, examine the distributional properties of the variables, and identify the presence of outliers.

The Variance Inflation Factor (VIF) was calculated for each indicator to quantify the severity of multicollinearity. A VIF value exceeding 5 or 10 is typically considered problematic, indicating high correlation with other predictors. The VIF results indicate that multicollinearity among the selected indicators remains within acceptable limits. For most variables, VIF values are below the commonly used threshold of 5, suggesting that multicollinearity is not severe. Although GDP (VIF = 5.08) and freight transport (VIF = 6.53) slightly exceed this threshold, these values do not compromise the analysis.

PCA is explicitly designed to address correlated variables by transforming them into orthogonal components. Therefore, the presence of moderate multicollinearity does not invalidate the use of PCA, rather, it reinforces the relevance of a dimension-reduction approach to manage the existing correlation structure and to avoid unstable or arbitrary weighting in the construction of the composite index. Overall, the low to moderate VIF levels indicate that each indicator contributes meaningful and non-redundant information, confirming the suitability of the dataset for PCA-based analysis.

Table 4
Statistical diagnostic tests prior to PCA.

Indicator	VIF Value	Number of Outliers	Skewness	Kurtosis
REC	4.29	25	2.16	3.85
RCO_2	2.19	10	−3.24	9.99
RTF	4.41	31	2.48	6.25
MR	3.55	0	−0.36	−0.74
GDP	5.08	0	0.74	−0.26
FTV	6.53	31	1.74	1.62

Outliers were identified using the Interquartile Range (IQR) method, where observations falling outside 1.5 times the IQR above the third quartile or below the first quartile are flagged. The analysis reveals a notable presence of outliers, particularly in Road Traffic Fatalities (31), Freight Transport Volume (31), and Road Energy Consumption (25). This pattern is expected in cross-country panel data, where large, developed economies often exhibit values substantially higher than smaller economies, leading to naturally skewed distributions. Since the data were normalized prior to PCA, the influence of these extreme values on the final index is mitigated. Moreover, as PCA aims to capture the structural variance across the entire dataset, retaining these outliers is important, as they represent genuine, albeit extreme, observations of the underlying phenomena.

The IQR-based outlier detection highlights a heterogeneous distribution of extreme values across indicators. Activity-related variables, such as freight transport volumes and road traffic fatalities, exhibit the highest number of outliers, reflecting substantial structural disparities in transport intensity and safety performance across countries. Energy consumption also shows a notable number of extreme observations, while emissions appear more concentrated. By contrast, no outliers were detected for motorization rate and GDP, suggesting relatively bounded and homogeneous distributions within the sample.

Overall, the identified outliers reflect genuine structural differences rather than data anomalies and were therefore retained for subsequent analysis. The absence of outliers for certain indicators does not indicate a lack of variability but rather illustrates the robustness of the IQR method when applied to bounded or widely dispersed distributions. Importantly, these extreme values are country- and year-specific rather than systematic and correspond to real-world conditions. Consequently, retaining them preserves the informational richness of the dataset, while the use of normalized indicators and PCA mitigates their potential influence on the composite index.

The distribution characteristics of the six indicators were examined using Skewness and Kurtosis to assess potential non-normality. The results confirm the presence of significant non-normality for most indicators, characterized by skewness and, in some cases, excess kurtosis. Such distributional features reflect strong asymmetries between countries with very high and very low transport performance and are typical of macro-panel sustainability data. Importantly, these deviations from normality do not violate the assumptions of PCA, which is a non-parametric technique based on the covariance matrix and is robust to such distributional irregularities.

The use of normalized indicators further ensures that scale differences do not unduly influence the analysis, allowing PCA to effectively capture the underlying dimensions of the data structure despite non-normal distributions. Overall, the observed non-normality is consistent across both environmental and economic indicators and reflects genuine

structural heterogeneity and development gaps between countries. Consequently, PCA applied to standardized variables remains an appropriate and robust analytical technique under these conditions.

4.3. PCA suitability analysis

To validate the methodological choice of applying PCA to the pooled panel dataset, we conducted formal tests for sampling adequacy. The suitability of the data for PCA relies on the presence of sufficient correlation among the indicators. This was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity.

The KMO index evaluates the proportion of variance among variables that might be common variance, with higher values indicating that PCA is appropriate. Bartlett's test examines whether the correlation matrix significantly differs from an identity matrix, ensuring that meaningful relationships exist between variables. Together, these tests provide a statistical foundation to justify the application of PCA and guarantee the reliability of the resulting component structure in capturing the underlying dimensions of transport sustainability.

As shown in Table 5, the KMO measure of sampling adequacy is 0.8, This value indicates that the data are suitable for factor analysis.

The KMO value of 0.807 indicates that the sample is well-suited for factor analysis, reflecting a high degree of common variance among variables. Values between 0.8 and 0.9 are considered "meritorious," confirming that the data structure is adequate for extracting latent factors. The Bartlett's test of sphericity shows a chi-square value of 1720.294 with 15 degrees of freedom and a p-value of 0.000, indicating statistically significant correlations among the variables. Together, these results confirm that the dataset meets the assumptions necessary for factor analysis, allowing us to confidently apply PCA. The high KMO and significant Bartlett's test suggest that the extracted factors will meaningfully summarize the observed variance, and that multicollinearity among variables is adequate but not excessive.

Bartlett's test was highly significant (chi-square = 1720.294, $p < 0.05$), confirming that the variables are sufficiently correlated. These results demonstrate that the necessary assumptions for factor analysis are met, allowing us to proceed with the examination of the correlation matrix and the application of Principal Component Analysis (PCA) with confidence.

The correlation matrix presented in Table 6 examines the relationships between energy consumption (CEnerg), carbon monoxide emissions (ECO), the number of road accident fatalities (NbDc), motorization rate (TM), GDP per capita (GDP), and freight transport (TRMR). Pearson correlation coefficients indicate the strength and direction of the relationships between these variables.

The correlation analysis reveals several important relationships among the key transport sustainability indicators. REC shows a strong positive correlation with carbon monoxide emissions (0.879) and freight transport (0.824), reflecting the central role of fossil energy use and logistics in environmental impacts. It is also strongly associated with road accident fatalities (0.757), suggesting that energy-intensive transport activities contribute to higher traffic risks. Interestingly, energy consumption exhibits weak negative correlations with motorization rate (−0.293) and GDP per capita (−0.250), indicating that higher energy use is not necessarily linked to more vehicles per capita or higher economic output, possibly due to energy efficiency measures or reliance on heavy vehicles.

Table 5
KMO index and Bartlett's test.

Measure	Value	Notes
KMO measure of sampling adequacy	0.807	It indicates meritorious sampling adequacy (values 0.8-0.9 are considered good): sufficient correlations for factor extraction.
Bartlett's test of sphericity - Approx. Chi-square	1720.294	A high chi-square value indicates that variables are significantly correlated, satisfying the prerequisite for factor analysis.
df	15	Degrees of freedom for Bartlett's test: it defines the reference distribution for the chi-square statistic.
Significance (p-value)	0.000	$p < 0.05$ indicates the test is statistically significant: Correlations between variables are not zero and factor analysis is justified.

Table 6
Correlation matrix.

	REC	RCO_2	RTF	MR	GDP	FTV
REC	1.000	0.879	0.757	−0.293	−0.250	0.824
RCO_2	***	1.000	0.770	−0.217	−0.165	0.850
RTF	***	***	1.000	0.000	0.068	0.818
MR	***	***	***	1.000	0.661	−0.126
GDP	***	***	***	***	1.000	−0.039
FTV	***	***	***	***	***	1.000

RCO_2 are highly correlated with freight transport (0.850) and accident fatalities (0.770), underscoring the dual environmental and social impacts of polluting transport activities. Weak negative correlations with motorization rate (−0.217) and GDP (−0.165) suggest that vehicle density and economic output are less important drivers of emissions, potentially reflecting the influence of cleaner technologies or regulatory frameworks. Road Traffic Fatalities (RTF) are strongly linked to freight transport (0.818), highlighting the safety risks associated with increased heavy vehicle traffic, while showing no meaningful correlation with motorization rate or GDP per capita.

TR, in turn, is moderately correlated with GDP per capita (0.661), consistent with the expectation that economic development fosters higher private vehicle ownership but shows little connection to freight transport (−0.126). Finally, GDP per capita exhibits negligible correlation with freight transport (−0.039), suggesting that economic output alone does not drive freight activity in this sample. Overall, freight transport emerges as a key factor influencing energy consumption, CO_2 emissions, and road safety, highlighting its central role in the sustainability challenges of road transport systems.

The correlation matrix highlights that freight transport is central to energy, environmental, and safety challenges. It is strongly linked to higher energy consumption, CO_2 emissions, and accident fatalities. While GDP and motorization rate are related, they appear less influential on energy consumption and freight transport. These findings suggest that policies aimed at improving energy efficiency and road safety should focus primarily on the freight transport sector and promote cleaner technologies and sustainable logistics practices.

Table 7 presents a summary of the main diagnostic test results.

The diagnostic tests confirm the statistical soundness and methodological relevance of the dataset used to construct the CRTSI. Raw indicators exhibit strong dispersion and scale heterogeneity, particularly for GDP and freight transport, which validates the need for normalization prior to aggregation. High VIF values indicate substantial correlations among indicators, a condition that is problematic for regression analysis but explicitly required for Principal Component Analysis, which exploits shared variance to extract latent sustainability dimensions. The IQR-based outlier detection highlights a limited number of extreme observations that reflect genuine structural differences across countries rather than data inconsistencies. Distributional diagnostics reveal non-normality and asymmetry, a common feature of cross-country transport data, which does not undermine the PCA framework.

4.4. PCA-based index construction

After verifying the KMO test and analyzing the correlation matrix,

Table 7
Summary of diagnostic and validation test results.

Test Category	Indicator/ Method	Result	Interpretation
Descriptive statistics (raw data)	Dispersion (Std. Dev.)	High for GDP and FTV; moderate for RCO_2 and RTF	Strong cross-country heterogeneity and scale effects
	Range (Min–Max)	Wide ranges for all indicators	Justifies normalization prior to aggregation
Multicollinearity	Variance Inflation Factor (VIF)	**REC** (4,29), RCO_2 (2,19), RTF (4,41), **MR** (3,55), **GDP** (5,08), **FTV** (6,53)	moderate multicollinearity; acceptable and desirable for PCA
Outlier detection	IQR method	Outliers detected mainly in Freight transport and Road fatalities.	Outliers reflect structural differences, not data errors
Distribution properties	Skewness	Non-zero skewness for most indicators (especially emissions and fatalities)	Asymmetric distributions typical of macro-panel data
	Kurtosis	Excess kurtosis for CO_2 emissions and fatalities	Presence of extreme values
PCA suitability	Correlation structure	Dense correlation matrix (confirmed by high VIFs)	Data appropriate for dimensionality reduction

we proceed to determine the weights of the indicators through Principal Component Analysis (PCA). Table 8 presents the eigenvalues, percentage of variance, and cumulative variance explained by each principal component. The table allows us to assess the contribution of each component to the total variance and to determine the number of components to retain for further analysis.

The first principal component accounts for **58.76%** of the total variance, while the second adds **27.68%,** resulting in a cumulative variance of **86.44%.** The remaining components have eigenvalues below 1 and each explains less than 6% of the variance, indicating that their contribution is negligible. Therefore, the first two components capture most of the information in the dataset and represent the most relevant dimensions for subsequent analysis.

The scree plot (Fig. 4) illustrates the eigenvalues of the principal components, with the vertical axis (Y-axis) representing eigenvalues and the horizontal axis (X-axis) representing component numbers. The curve shows a steep drop between the first and second components, followed by a gradual flattening. The point at which the curve levels off, known as the "elbow" or inflection point, indicates the optimal number of components to retain.

In this analysis, the elbow occurs after the second component, confirming that the first two components capture the most substantial share of the variance. Components beyond this point contribute only marginally and are therefore less informative. This conclusion is consistent with Kaiser's criterion, which recommends retaining components with eigenvalues greater than 1.

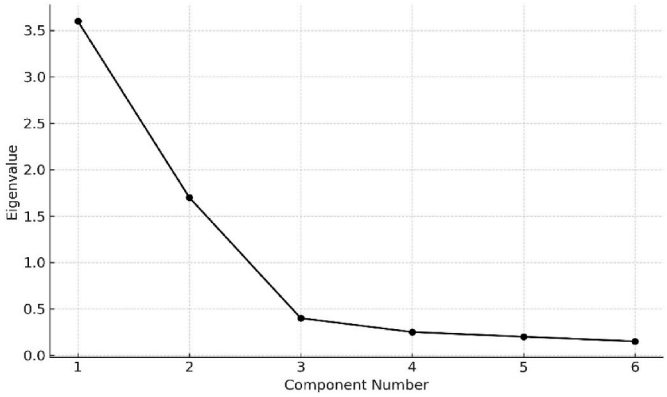


Fig. 4. Scree plot.

The scree plot presents the eigenvalues of the components against their respective component numbers. The slope declines sharply from the first to the second component, after which the curve flattens from the third component onward, indicating the elbow point. This confirms Kaiser's criterion, which recommends retaining only components with eigenvalues greater than 1. Consequently, only the first two components should be considered.

These results suggest that the original indicators can be grouped into two synthetic dimensions, enabling a meaningful simplification of the dataset without substantial information loss. Moreover, weights can be assigned to each indicator based on their factor loadings in the component matrix, which will serve as the basis for constructing composite indices.

The component matrix (Table 9) will help to identify the most representative indicators for each principal component (i.e., those with high positive or negative loadings) and then detect less contributive variables (loadings close to zero), which may either be excluded or assigned minimal weight. Thus, PCA not only functions as a powerful dimension-reduction tool but also provides an objective approach for assigning weights to indicators when developing composite indices.

Table 9 presents the factor loadings of each indicator on the first and second principal components. Factor loadings represent the correlation between each original variable and the extracted components. High absolute values (close to 1 or -1) indicate that an indicator is strongly associated with the corresponding component, while values near 0 indicate weak representation.

From the table, it is evident that some indicators are strongly associated with one component, while others are more related to the second component. This allows us to identify which variables contribute most to each principal component and to assign appropriate weights for constructing composite indices.

The component matrix shows the factor loadings of each indicator on the first and second principal components. The PCA reveals two dominant and complementary dimensions that can be interpreted as transport pressure and economic–institutional capacity, jointly explaining most of the variance in the data.

Table 8
Total variance explained (extraction method: PCA).

Component	Eigenvalue (Total)	% of Variance	Cumulative %
1	3.526	58.763 %	58.763 %
2	1.661	27.675 %	86.438 %
3	0.339	5.652 %	92.090 %
4	0.210	3.508 %	95.598 %
5	0.150	2.506 %	98.104 %
6	0.114	1.896 %	100.000 %

Table 9
Component matrix (extraction method: PCA).

Indicator	Component 1	Component 2
Road Energy Consumption	0.946	0.00
Road Transport CO_2 Emissions	0.944	0.00
Road Traffic Fatalities	0.865	0.323
Motorization Rate	−0.295	0.856
GDP	−0.224	0.885
Freight Transport Volume	0.925	0.186

- **Component 1- Transport and environmental pressure (≈ 65% of total explained variance):** This component is driven by very high loadings on **road energy consumption (0.946)**, **CO_2 emissions (0.944)**, and **freight transport volume (0.925)**, combined with a strong contribution from **road traffic fatalities (0.865).** It captures the intensity and pressure exerted by road transport systems on the environment, infrastructure, and public safety, reflecting the scale and externalities of transport activity. As a result, pressure-related indicators account for approximately two-thirds of the overall CRTSI weight.
- **Component 2- Economic and social dimension (≈ 35% of total explained variance):**The second component is dominated by **GDP per capita (0.885)** and **motorization rate (0.856)**, representing countries' economic capacity and access to private mobility. This dimension reflects enabling conditions, such as income level, investment capacity, and mobility access, rather than direct sustainability pressures, and contributes roughly one-third of the composite index weight. This component likely reflects the relationship between economic growth, vehicle ownership, and living standards.

Overall, the resulting weighting structure shows that the CRTSI places greater emphasis on transport-related pressures while still accounting for economic and mobility capacity. This pressure–capacity balance is consistent with sustainability assessment frameworks that prioritize the mitigation of environmental and safety externalities, while recognizing the role of economic context in shaping transport outcomes.

4.5. Empirical results of CRTSI

This step involves combining the weighted indicators into a single value that summarizes the overall performance or status of each country in terms of transport sustainability.

4.5.1. Global average CRTSI trend

Fig. 5 illustrates the evolution of the average CRTSI value across all 32 countries over the 11-year period.

The red line clearly shows a moderate but consistent upward trend in the global average CRTSI, rising from approximately 0.66 in 2011 to around 0.71 in 2021. This indicates that, on average, road transport sustainability has improved across the sample of countries.

The increase is not perfectly linear: a noticeable jump occurs between 2014 and 2015, while the trend stabilizes or slightly declines between 2020 and 2021, likely reflecting the impacts of the COVID-19 pandemic and subsequent recovery dynamics.

The shaded gray area represents the full range of CRTSI values observed each year (from the minimum to the maximum country score). The width of this band remains relatively large and consistent throughout the period, highlighting a persistent and significant heterogeneity in sustainability performance among countries.

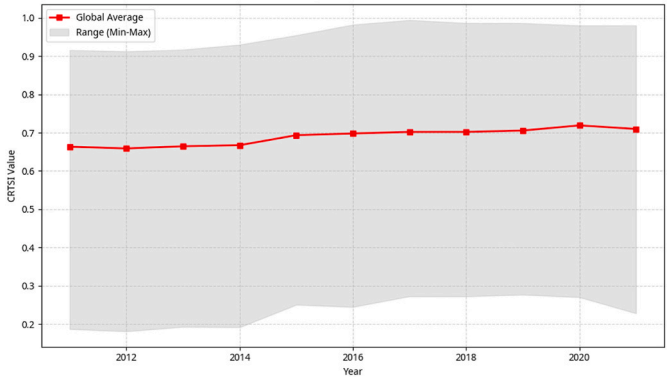


Fig. 5. Global average CRTSI trend (2011-2021).

4.5.2. Heatmap of CRTSI values by country and year

The heatmap in Fig. 6 provides a comprehensive, at-a-glance view of the entire dataset, allowing for easy pattern recognition across both countries and time.

The vertical color bands reveal the relative performance of each country. Nations positioned at the top, such as Iceland and Norway, consistently appear in dark blue, reflecting high CRTSI values throughout the decade. In contrast, countries at the bottom, including Germany, France, Italy, and Turkey, are represented by lighter shades, indicating lower scores. Over time, most countries exhibit a gradual shift from lighter shades on the left (2011) to darker shades on the right (2021), visually confirming the generally positive temporal trend in road transport sustainability.

The heatmap also highlights the most notable anomalies. Germany, France, Italy, and the United Kingdom start with relatively low values but darken rapidly over time, indicating high growth rates. Conversely, Turkey displays a persistently light band, which remains the same or even slightly lightens toward 2021, reflecting a negative or stagnant trend that contrasts sharply with most countries. Overall, the heatmap effectively synthesizes two key findings: a clear overall improvement in CRTSI over time (evidenced by the darkening toward the right) and a wide, persistent disparity between the highest and lowest performers (indicated by vertical color variation).

Compared to 2011, the distribution in 2021 shows a slight rightward shift, suggesting general improvements in transport sustainability across most countries.

As shown in Fig. 7, the evolution of CRTSI values between 2011 and 2021 reveals divergent sustainability trajectories across countries. From a temporal perspective, the comparison between 2011 and 2021 shows a general upward trend in CRTSI values for most countries, suggesting overall progress in road transport sustainability. However, the relative rankings remain largely unchanged, indicating that improvements have occurred in parallel rather than through convergence. This stability in rank positions highlights the structural nature of cross-country differences in road transport sustainability.

France (+0.127), Germany (+0.160), the United Kingdom (+0.131), Italy (+0.118), and Spain (+0.050) stand out as the most dynamic performers, recording the strongest improvements in their transport sustainability levels **(Top 5 gainers)**. In contrast, Turkey (−0.059) experienced a clear decline, while Lithuania (−0.002) showed almost no progress **(Top 2 losers)**. North Macedonia (+0.008), Albania (+0.024), and Bulgaria (+0.006) registered only marginal gains, reflecting limited structural transformation. These disparities may be attributed to heterogeneous policy efforts, investment capacities, and the varying pace of energy transition and road safety reforms across countries. Tunisia shows a slight improvement from 2011 (0.590) to 2021 (0.612), indicating incremental progress in transport sustainability.

4.5.3. Top 10 countries with highest CRTSI Growth (2011 2021)

For methodological reasons, this line chart (Fig. 8) focuses on the 10 countries that achieved the largest absolute increase in their CRTSI scores between 2011 and 2021.

The lines for countries such as Germany, the United Kingdom, France, and Italy exhibit the steepest upward slopes, highlighting their role as the primary drivers of the overall positive global trend. These nations have implemented policies or undergone changes that resulted in rapid improvements in their composite CRTSI.

It is important to consider the different starting points. Germany, France, and Italy began with relatively low CRTSI values (around 0.2 to 0.4), meaning their substantial absolute growth reflects a significant catch-up effort. In contrast, countries like Denmark and Iceland, which also feature among the top 10, started from an already high base (above 0.8). Their growth, although notable, represents further optimization from an advanced position. Most of these top-performing countries demonstrate a relatively smooth and continuous increase, suggesting sustained efforts rather than one-off improvements.

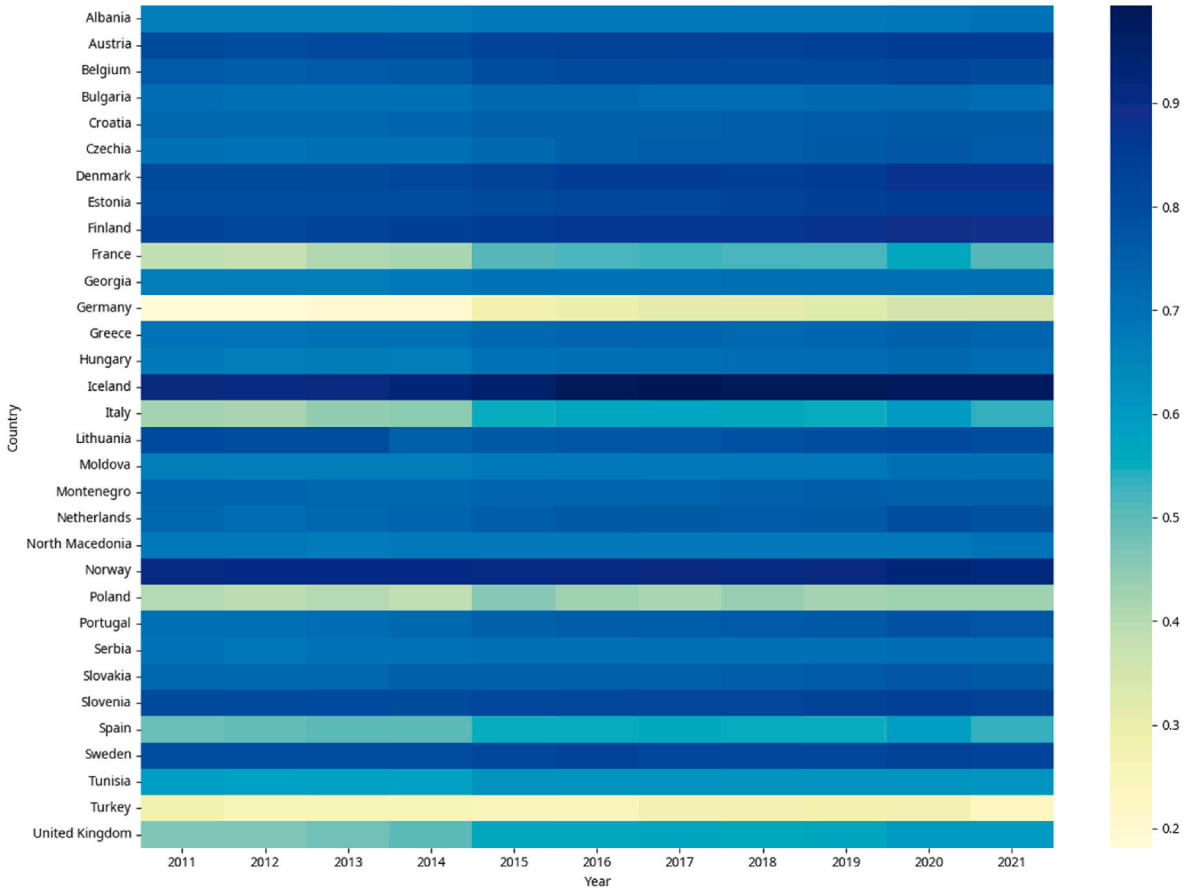


Fig. 6. Heatmap of CRTSI values.

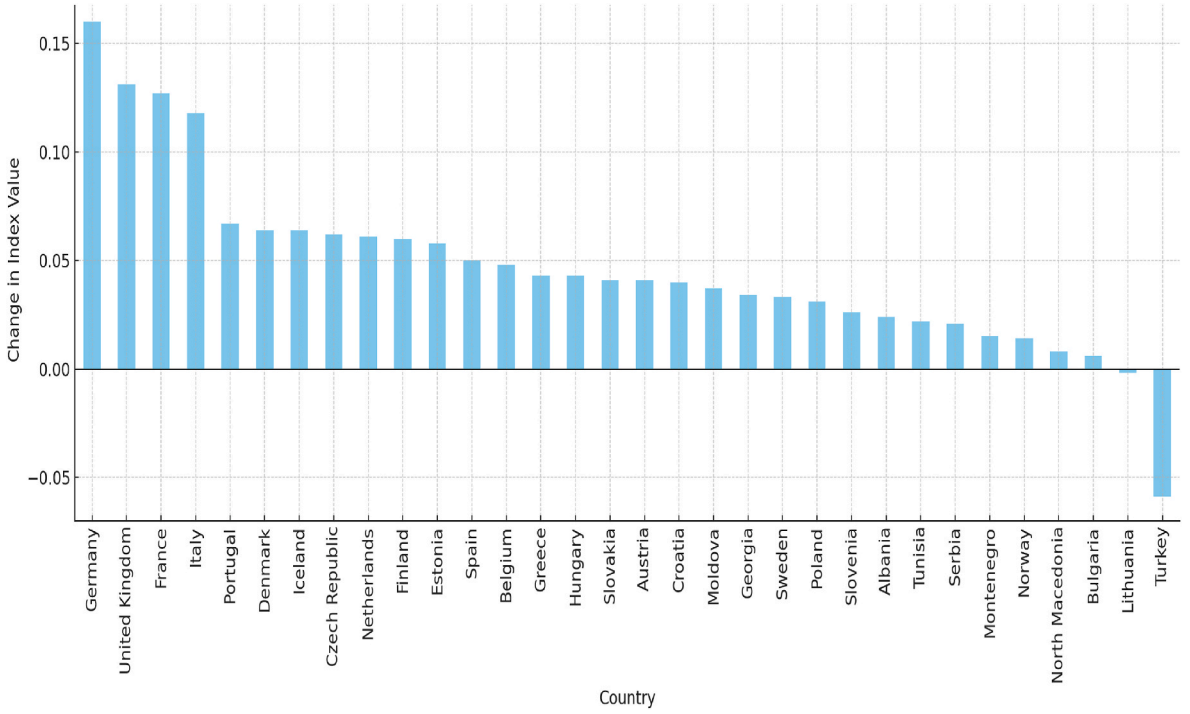


Fig. 7. Change in **CRTSI (2021 vs. 2011) by country**.

4.5.4. CRTSI rankings

Fig. 9 illustrates the ranking of CRTSI across countries in 2011 and 2021. It provides a visual representation of the composite index, facilitating the identification of countries leading or lagging in sustainable

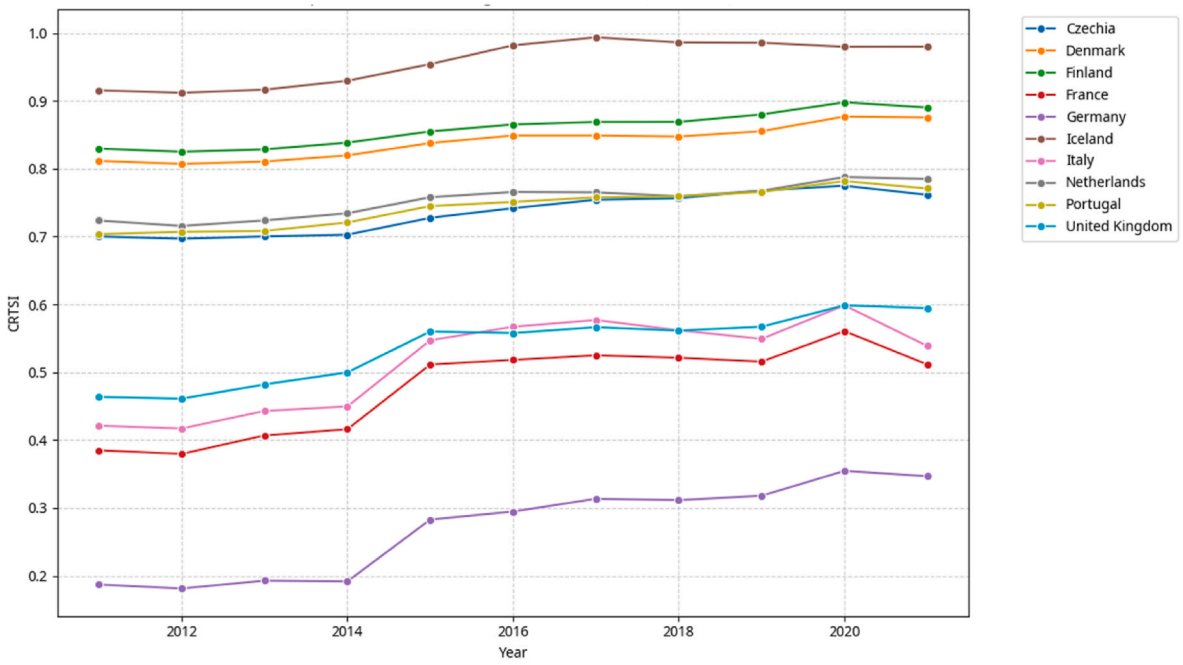


Fig. 8. Top 10 countries with highest CRTSI growth.

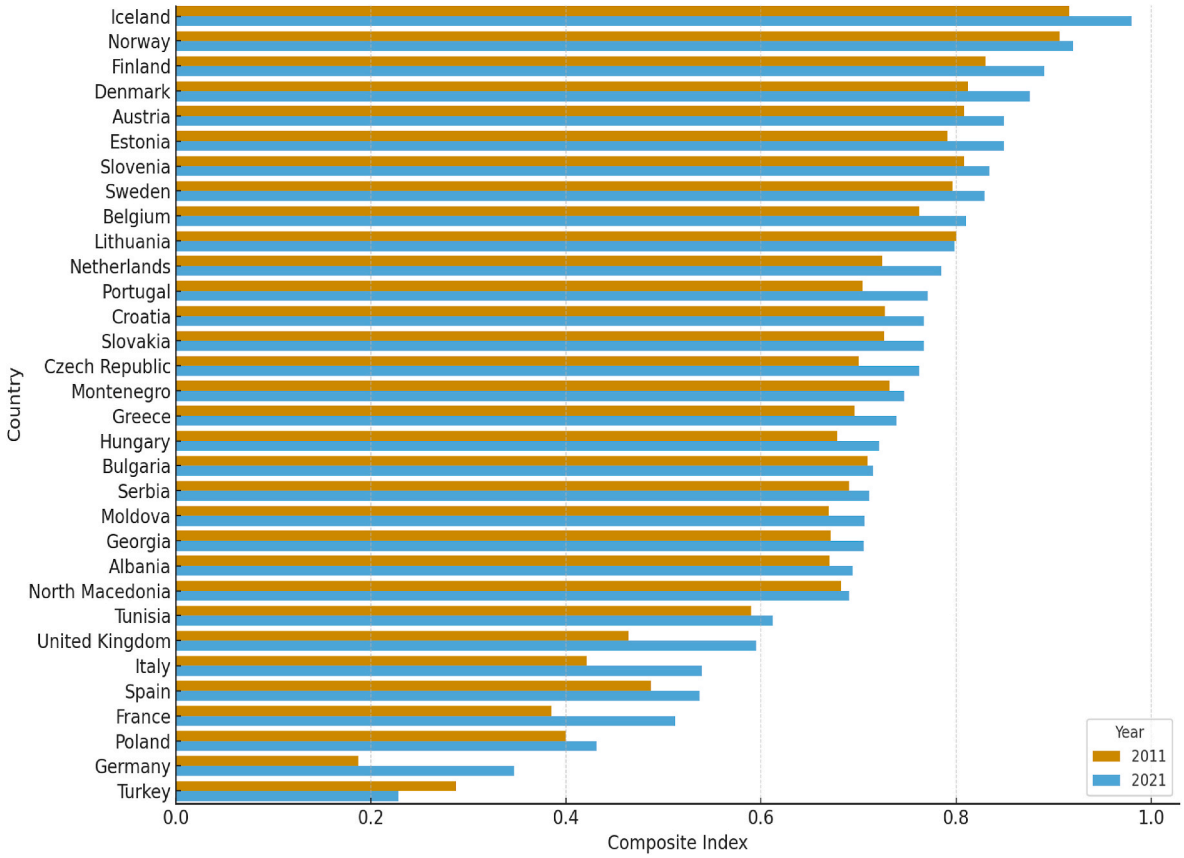


Fig. 9. Ranking of countries by CRTSI in 2011 and 2021.

transport.

4.6. Sensitivity analysis

To assess the stability of the CRTSI, two robustness checks were conducted. We evaluated the impact of the weighting method by constructing an alternative version of the CRTSI using equal weights for all six indicators. Rank concordance between the PCA-based CRTSI and the alternative indices was evaluated using Spearman's rank correlation coefficient (ρ). Additionally, comparisons between pooled-period PCA

loadings and base-year loadings were performed to assess temporal stability.

4.6.1. Sensitivity analysis: comparison with alternative weighting schemesnew

To formally assess the robustness of the CRTSI derived from PCA, a quantitative sensitivity analysis was performed. This analysis compares the CRTSI rankings obtained using the objective PCA-derived weights against those obtained from an alternative method: Equal Weighting (EW). The comparison is quantified using Spearman's Rank Correlation Coefficient (ρ), which measures the monotonic relationship between the rankings produced by the two different weighting schemes.

This result in Table 10 demonstrates a very high and statistically significant correlation between the two sets of rankings. This high degree of concordance confirms the strong robustness of the CRTSI. The implication is that the objective weights derived from the PCA, while statistically grounded in the data's variance structure, do not fundamentally change the overall ranking of countries compared to a simple, non-discriminatory equal weighting approach.

4.6.2. Sensitivity analysis (pooled vs. base year loadings)

To formally assess the implications of applying a pooled PCA to panel data, Table 11 presents a sensitivity analysis comparing the loadings of the first principal component (PC1) obtained from the pooled dataset with those derived from a single cross-sectional base year (2017).

The comparison reveals a high degree of stability between the loadings of the Pooled PCA and the Base Year PCA. The largest absolute difference is observed for the MR (0.0560) and GDP (0.0259), while the most influential indicators (Road Traffic Fatalities and Freight Transport Volume) show negligible differences (0.0015 and 0.0008, respectively). The minimal variation in the component loadings across the two approaches confirms the stability and representativeness of the Pooled PCA.

This comparative analysis validates the methodological decision to use the pooled dataset to extract the underlying structural cross-country patterns, as the weights derived from the entire time series are highly consistent with those from a single representative year. This confirms that the structural relationships between the indicators are stable over the observation period, justifying the use of a single, time-invariant weighting scheme.

5. Discussion of results

5.1. Cluster-based comparative analysis (2021)

To deepen the comparative interpretation of the CRTSI results, a cluster analysis was conducted for the year 2021 using K-Means Clustering algorithm, an unsupervised learning technique that partitions observations by minimizing within-cluster variance (MacQueen, 1967; Pedregosa, et al., 2011). The cluster analysis provides a powerful, data-driven segmentation that moves beyond simple linear ranking, offering policymakers targeted insights into the specific structural challenges faced by each group (Jain, 2010).

K-means is particularly suitable for composite indicators and sustainability indices, as it allows the identification of groups of countries with similar performance profiles, such as high, medium, and low sustainability clusters. Its simplicity, computational efficiency, and interpretability make it a preferred tool for benchmarking and comparative policy analysis in transport sustainability studies.

Table 10
Spearman's rank correlation coefficient.

Comparison	Spearman's ρ	Interpretation
PCA vs. Equal Weighting	0.9193	Very High Correlation (Strong Robustness)

Table 11
Stability of PCA loadings: Pooled panel data versus Base-Year Cross-Section (2017).

Indicator	Pooled Loadings (PC1)	Base Year 2017 Loadings (PC1)	Absolute Difference
Road Energy Consumption	0.5469	0.5356	0.0113
Road Transport CO_2 Emissions	0.1227	0.1161	0.0066
Road Traffic Fatalities	0.5704	0.5689	0.0015
Motorization Rate	−0.0632	−0.1192	0.0560
GDP	−0.1075	−0.1334	0.0259
Freight Transport Volume	0.5873	0.5865	0.0008

K-means clustering is an unsupervised machine learning technique widely used to classify observations into homogeneous groups based on similarity. The method aims to partition N observations into K clusters, where each observation belongs to the cluster with the nearest mean (centroid). The algorithm iteratively minimizes the Within-Cluster Sum of Squares (WCSS), defined as the sum of the squared distances between each observation and the centroid of its assigned cluster (MacQueen, 1967; Hartigan and Wong, 1979).

Formally, the objective function is expressed as:

$$\min_{C} \sum_{k=1}^{K} \sum_{x \in C_k} \left| |x - \mu_k| \right|^2 \tag{8}$$

Where C_k is the k-th cluster, μ_k is the centroid (mean vector) of cluster C_k, and x is an observation vector. By minimizing the WCSS, the algorithm ensures that countries within the same cluster are maximally similar to each other, while being maximally dissimilar from countries in other clusters.

The algorithm proceeds iteratively through two main steps:

- **Assignment**, where each observation is allocated to the nearest centroid based on Euclidean distance; and
- **Update**, where cluster centroids are recalculated as the mean of assigned observations.The process continues until convergence, typically when cluster memberships or centroid positions stabilize.

Prior to clustering, the data for the year 2021 was standardized using Z-scores to ensure that all six indicators contribute equally to the distance calculation, preventing indicators with larger numerical ranges (e.g., GDP) from dominating the clustering process.

The optimal number of clusters (K) was determined using the Elbow Method. This method plots the WCSS as a function of the number of clusters (K), with the optimal K being the point where the marginal gain in reducing WCSS sharply decreases, resembling an “elbow” in the plot. Based on this diagnostic, three clusters ($K = 3$) were selected, providing a meaningful balance between granularity and interpretability, aligning with the three tiers of performance observed in the descriptive analysis (top, middle, and bottom performers).

Based on the Elbow Method, three clusters ($K = 3$) were selected, providing a meaningful balance between granularity and interpretability, aligning with the three tiers of performance observed in the descriptive analysis. The following table (Table 12) presents the mean values (centroids) of the indicators for each of the three clusters. The CRTSI score has been corrected to reflect the convention where 1 = Best Performance and 0 = Worst Performance.

The results reveal a clear three-cluster structure.

- **Cluster 2:** High-Income, High-Score (The Sustainability Leaders): This cluster, comprising countries like Norway, Iceland, Denmark, and Finland, is characterized by the highest average CRTSI score (0.868) and the highest average GDP (61,882.2). Despite a high

Table 12
Results of cluster-based comparative analysis (2021).

Cluster	N	Average CRTSI Score (1 = Best)	Road Energy Consumption	Road Transport CO_2 Emissions	Road Traffic Fatalities	Motorization Rate	GDP	Freight Transport Volume
0: Developing Economies	17	0.847	2895.35	96.01	410.58	407.98	15677	30423.5
1: High-Volume, Low-Score	6	0.245	33110.10	95.30	2920.17	446.31	31638.3	268763.0
2: High-Income, High-Score	9	0.868	5720.54	92.50	413.56	545.88	61882.2	39555.0

Motorization Rate, this group exhibits the lowest average Emissions and a moderate Number of Deaths, confirming their success in decoupling economic prosperity from environmental and social costs through advanced policy and technology adoption.

- **Cluster 0:** Developing Economies (The Mid-Range): This is the largest cluster, encompassing countries from Central/Eastern Europe and the Mediterranean (e.g., Georgia, Turkey, Montenegro). This group is defined by the lowest average GDP and Energy Consumption. While their CRTSI score is relatively high (0.847), this is largely due to the low absolute scale of their transport activity. The challenge for this cluster lies in maintaining sustainability as their economies and transport demands grow.
- **Cluster 1:** High-Volume, Low-Score (The Structural Challenge): This cluster, including major economies like Germany, France, and Italy, is defined by the highest average values for Freight Transport (268,763.0) and Energy Consumption (33,110.10), resulting in the lowest average CRTSI score (0.245). This group highlights the structural burden of managing large, industrial-scale transport activity. The inclusion of high-GDP countries here demonstrates that the sheer volume of transport activity, particularly freight, creates a structural drag on overall sustainability performance.

The cluster structure is further illustrated through key scatter plots, which provide visual evidence of the identified structural patterns. For methodological reasons, we interpret the relationship between the CRTSI and its three constituent dimensions, particularly road freight transport activity (economic dimension), road transport CO_2 emissions (environmental dimension), and road traffic fatalities (social dimension), as visualized in the scatter plots. The analysis is structured around the three identified clusters: Cluster 2 (high-income, high-score countries), Cluster 1 (high-volume, low-score countries) and Cluster 0 (developing economies).

The scatter plot in Fig. 10, illustrating the relationship between the CRTSI and Road Freight Transport Activity reveals a complex pattern, primarily driven by the scale of the economy.

A strong negative correlation is observed, confirming that the volume of freight transport is a major determinant of the CRTSI score. Countries in the Cluster 2 (e.g., Norway, Iceland) generally exhibit moderate to low freight activity. Their high CRTSI scores suggest that they have successfully mitigated the environmental and social costs associated with necessary freight volumes, often through modal shift (sea/rail) or the adoption of cleaner technologies. The cluster 1 (Structural Challenge), which includes major European economies (e.g., Germany, Poland, France), is characterized by the highest absolute volumes of freight transport. The scatter plot shows that despite having relatively high GDPs, these countries tend to have lower CRTSI scores. This indicates that the sheer scale of their economic activity, particularly road-based logistics, imposes a significant structural burden on their overall sustainability performance, primarily through energy consumption and emissions. The plot suggests that policy efforts aimed at shifting freight from road to rail/sea, or improving the energy efficiency of the freight sector, would have the most substantial positive impact on the CRTSI score for Cluster 1. Countries in cluster 0 (Developing Economies) show low to moderate freight activity, often correlating with lower CRTSI

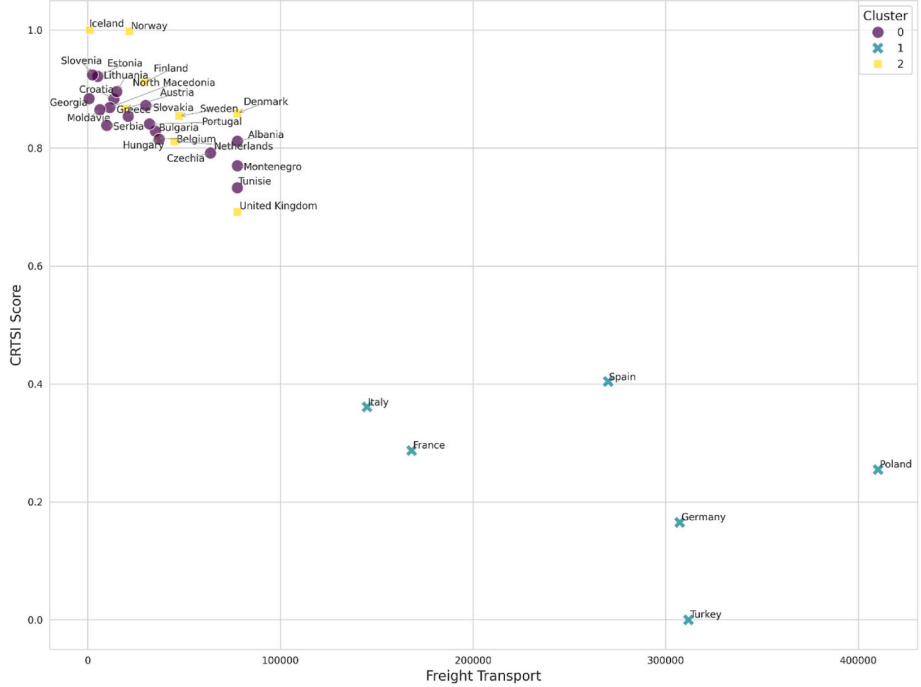


Fig. 10. Scatter plot of CRTSI scores versus road freight transport activity.

scores. The challenge here is not necessarily the volume, but the efficiency and safety of the existing transport infrastructure.

The relationship between the CRTSI and Road Transport CO_2 Emissions is strongly negative, confirming the critical role of the environmental pillar in the index construction (Fig. 11).

Countries in cluster 2 (Sustainability Leaders) occupy the top-left quadrant of the scatter plot, demonstrating the lowest levels of CO_2 emissions coupled with the highest CRTSI scores. This is a clear empirical validation of their successful decoupling of transport activity from carbon impact, often achieved through high penetration of electric vehicles and stringent fuel efficiency standards. For Cluster 1 (Structural Challenge), countries in this cluster are positioned in the middle-to-lower range of the CRTSI score, corresponding to high absolute emission levels. The scatter plot illustrates that their large transport systems result in substantial environmental footprints, making the reduction of CO_2 emissions a primary policy challenge for this group. Cluster 0 (Developing Economies) is scattered across the middle range of the plot. While their absolute emissions are lower than cluster 1, their CRTSI scores are also lower, suggesting that the environmental challenge is compounded by deficiencies in the social and economic dimensions. The plot highlights that while emissions are a critical component, the CRTSI score is not solely determined by them, as other factors (safety, GDP) contribute significantly.

In Fig. 12, the scatter plot comparing the CRTSI with Road Traffic Fatalities reveals a clear inverse relationship, highlighting the importance of safety for overall sustainability.

In Cluster 2 (Sustainability Leaders), countries are consistently located at the extreme left of the plot, demonstrating the lowest fatality rates and the highest CRTSI scores. This reflects the success of comprehensive Vision Zero strategies and robust road safety policies, making the social dimension a key differentiator for the top performers.

Cluster 1 (Structural Challenge) shows a moderate to high number of fatalities, contributing significantly to their lower CRTSI scores. The high volume of traffic and the complexity of their road networks present ongoing safety challenges. Cluster 0 (Developing Economies) is characterized by the highest fatality rates, placing them at the lower end of the CRTSI scale. The scatter plot visually confirms that poor road safety is a dominant factor dragging down the overall sustainability performance of these developing economies, underscoring the urgent need for investment in safety infrastructure and enforcement.

The visual analysis of the scatter plots confirms that the CRTSI effectively captures the multi-dimensional nature of transport sustainability. Countries, notably those with large populations and high traffic volumes, are penalized heavily by high fatality rates, which significantly drags down their overall CRTSI score.

5.2. Validation and benchmarking of CRTSI rankings

The external validity of the CRTSI rankings is assessed through a descriptive benchmarking exercise against two widely recognized international indicators: the Environmental Performance Index (EPI) and the Global Competitiveness Index (GCI).

According to the Environmental Performance Index 2022 (EPI), which scores countries on environmental health and ecosystem vitality on a 0–100 scale, many of the top-ranked CRTSI performers also achieve high environmental scores. For example, Denmark (77.9), Finland (76.5), Sweden (72.7), Iceland (62.8) and France (62.5) all feature prominently in the EPI rankings, placing them among the better performers globally on environmental criteria. By contrast, countries lower in the CRTSI distribution, such as Norway (59.3) and Italy (57.7), exhibit comparatively lower EPI scores. These data illustrate that countries with high CRTSI scores generally correspond to stronger environmental performance in the EPI.

Similarly, partial concordance is observed with the GCI, especially among high-income economies. However, notable divergences emerge for countries that rank well in competitiveness but poorly in the CRTSI, such as Germany and Poland. These discrepancies underscore the added value of the CRTSI, as it captures road-transport-specific sustainability dimensions that are not fully reflected in aggregate competitiveness indicators.

In the 2019 GCI rankings, several countries that rank highly in the CRTSI also demonstrate above-average competitiveness scores: Germany (81.8, global rank ~7th), Denmark (81.2, ~8th), Sweden (81.2, ~9th) and Finland (80.2, ~11th) all score well above the global average of roughly 60.7 in the GCI 4.0 framework. Meanwhile, countries positioned lower in the CRTSI such as Spain (75.3, ~23rd), France (78.8, ~15th) and Italy (~around 40th) show relatively more heterogeneous competitiveness outcomes. These benchmarks reflect that high road

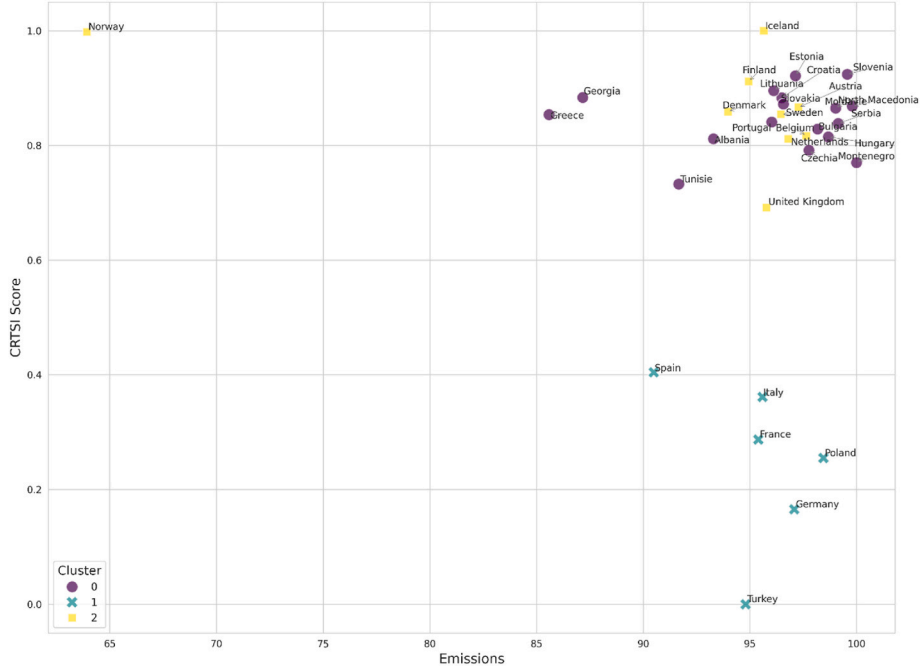


Fig. 11. Scatter plot of CRTSI scores versus road transport CO_2 emissions.

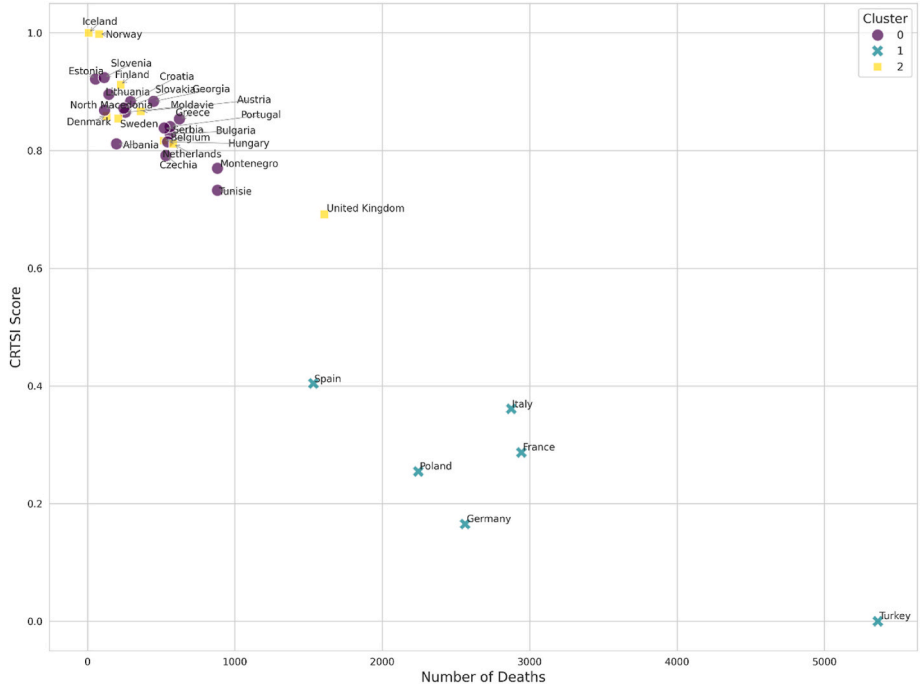


Fig. 12. Scatter plot of CRTSI scores versus road traffic fatalities.

transport sustainability performance tends to coincide with strong economic fundamentals, though the alignment is not perfect and underscores the unique focus of the CRTSI on transport-specific sustainability outcomes.

At first glance, the dominance of Nordic countries and the relatively low ranking of major economies such as Germany, Poland, or Turkey may appear counterintuitive given their advanced transport infrastructure. However, this apparent paradox is resolved once the road-transport-specific focus of the CRTSI is considered.

Countries with high CRTSI rankings also display high environmental and institutional performance in external benchmarks. For instance, Nordic frontrunners consistently achieve high scores in the Environmental Performance Index (EPI) and rank among the most competitive economies according to the Global Competitiveness Index (GCI). Conversely, several lower-ranked CRTSI countries exhibit strong economic competitiveness but weaker environmental outcomes in the road transport sector.

Together, these descriptive benchmarks show that top CRTSI performers also tend to score highly on established environmental and economic indices, thereby validating the plausibility and robustness of the CRTSI as a meaningful comparative metric. At the same time, divergences, particularly for some highly competitive economies, highlight how the CRTSI captures distinct aspects of sustainable transport performance not fully reflected in broader competitiveness assessments.

Overall, the benchmarking exercise confirms that the CRTSI produces rankings that are both externally coherent and analytically distinct. While aligned with broader sustainability and competitiveness metrics, the CRTSI provides a more targeted and policy-relevant assessment of road transport sustainability, thereby complementing existing international indices rather than duplicating them.

5.3. Validation against external sustainability frameworks

While the Composite Regional Transport Sustainability Index (CRTSI) is a novel construct, its analytical credibility is reinforced by its strong coherence with internationally recognized sustainability benchmarks. The objective of this validation is not to replicate existing frameworks, but to demonstrate that the CRTSI results are consistent with established reference points regarding transport sustainability performance. We proceed by validating the coherence (construct validity) of the CRTSI rankings, trends, and country profiles against three major external benchmarks: the ITF/OECD framework, EU monitoring goals, and the UN Sustainable Development Goals (SDGs).

5.3.1. Coherence with ITF/OECD transport sustainability benchmarks

CRTSI's ability to differentiate performance is strongly consistent with detailed country assessments published by the International Transport Forum (ITF) and the OECD. The CRTSI identifies Iceland (0.980), Norway (0.920), Finland (0.890), and Denmark (0.876) as the leading countries in 2021. This finding aligns perfectly with the established profile of Nordic nations, which are consistently recognized by the ITF for their strong environmental policies, high road safety standards (low fatalities per capita), and early adoption of sustainable transport technologies. Their high scores reflect a successful decoupling of economic growth (GDP) from environmental pressures (Emissions and Energy Consumption).

Conversely, countries ranked at the lower end, such as Germany (0.347), Turkey (0.228), and Poland (0.431), are consistently highlighted in ITF and OECD reports for persistent challenges. For instance, the lower score for Germany is often attributed to high freight transport volumes and associated emissions, while Turkey and Poland face hurdles related to road safety and energy efficiency in their rapidly expanding transport sectors. CRTSI effectively captures these known structural weaknesses. This coherence confirms that the index captures meaningful and policy-relevant differences in road transport sustainability performance, supporting the construct validity of the CRTSI.

5.3.2. Alignment with European Union (EU) monitoring goals

CRTSI's structure and results provide a direct measure of progress toward the ambitious targets set out in the EU's Sustainable and Smart Mobility Strategy. The strong performance of the Nordic countries is directly linked to their superior alignment with the EU's goal of achieving a 90% reduction in transport-related greenhouse gas emissions by 2050. The moderate performance of most EU countries (e.g., Estonia, Belgium, Croatia, Slovenia, and Sweden) clustering in the mid-range reflects the ongoing, but incomplete, transition toward

sustainable transport policies across the bloc.

The high CRTSI scores of countries like Norway and Finland are heavily influenced by their exceptional road safety records, which are benchmarks for the EU's "Vision Zero" initiative. Conversely, the lower scores of countries like Turkey and Poland highlight areas where significant policy intervention is still required to meet EU safety standards.

5.3.3. Contribution to Sustainable Development Goals (SDGs)

CRTSI provides a regionalized, quantifiable metric for tracking several transport-related SDG targets, thereby contributing to the global monitoring agenda. As shown in Table 13, the country profiles observed are consistent with their known performance against these specific goals:

The strong convergence between the CRTSI rankings and external sustainability benchmarks reinforces the index's validity and its utility as a robust analytical instrument for transport policy analysis.

5.4. Contextual interpretation

This substantial heterogeneity observed in the CRTSI necessitates an examination of the policy, structural, and geographical mechanisms driving country performance. The gap between Nordic frontrunners and Central European laggards reflects not differences in wealth alone, but fundamentally divergent development pathways and policy choices.

5.4.1. The Nordic model: policy-driven decoupling

The high CRTSI scores of Iceland, Norway, and Finland are explained by a combination of mutually reinforcing factors. First, these countries exhibit a high penetration of renewable energy in road transport. In Norway, 88.9 % of all new passenger cars sold in 2024 were fully electric, placing the country at the forefront of the transition to zero-emission vehicles and contributing to reduced transport emissions. This substantially reduces per-capita energy consumption and road transport emissions.

Second, Nordic countries consistently record exceptionally low road traffic fatality rates, reflecting decades of integrated road safety strategies. According to latest World Health Organization estimates, Norway and Iceland report among the lowest mortality rates from traffic injuries in high-income countries (approximately ~2 deaths per 100,000 population), while Sweden similarly records very low fatality figures among comparable OECD nations.

Third, despite high income levels, motorization intensity is relatively contained through effective public transport provision, compact urban planning, and demand management policies. While Nordic countries maintain high GDP per capita, their motorization intensity (vehicles per inhabitant) does not escalate proportionally with income, partly due to strong urban planning and public transport policies that attenuate private vehicle dependency. Although the EU average is approximately 574 cars per 1000 inhabitants, some Nordic countries manage the balance between vehicle ownership and sustainable mobility options more effectively.

Together, these mechanisms illustrate a successful decoupling of road transport activity from environmental impact, confirming that sustainability leadership is primarily policy-driven rather than income-driven.

Table 13
Alignment between CRTSI indicators and SDGs.

SDG Target	CRTSI Indicator Alignment	Coherence with CRTSI Results
SDG 3.6 (Road Safety)	Road Traffic Fatalities	High-ranking countries (e.g., Norway) are leaders in reducing road fatalities, directly supporting this target.
SDG 7.3 (Energy Efficiency)	Road Energy Consumption	Countries with high CRTSI scores demonstrate better energy efficiency in transport, aligning with the goal of improving global energy efficiency.
SDG 9.1 (Sustainable Infrastructure)	Freight Transport volume and GDP	The lower scores of countries like Germany and Poland reflect the structural challenge of managing high-volume freight transport while maintaining sustainability, a key concern of SDG 9.1.
SDG 11.2 (Sustainable Urban Transport)	Motorization Rate	The high performance of the Nordic countries is often associated with policies that favor public and non-motorized transport, aligning with the goal of accessible and sustainable transport systems.

5.4.2. The Central European challenge: scale and structural constraints

In contrast, the lower CRTSI rankings of countries such as Germany and Poland are largely attributable to structural characteristics of their road transport systems. Germany's central position in Europe results in exceptionally high volumes of road freight transit, which, despite technological efficiency, translate into elevated absolute energy use and CO_2 Emissions. In 2024, Poland accounted for approximately 368 billion tonne-kilometres of road freight in the EU, nearly 20 % of the EU total, and Germany followed with about 281 billion (15 %).

Moreover, these countries have struggled to fully decouple road transport growth from fossil fuel dependence. In Germany, the transport sector accounted for about 20 % of total national CO_2 emissions, and a large majority of these emissions are from road traffic rather than rail or inland waterways. The limited deployment of congestion pricing, carbon road pricing, and strong modal shift incentives contribute to weaker performance on the environmental pillar of the CRTSI. This highlights a critical mechanism: economic efficiency and infrastructure quality alone do not guarantee road transport sustainability.

5.5. Accounting for scale and income effects in the CRTSI

CRTSI can be influenced by country size, population, and income levels. Smaller, high-income countries such as Iceland benefit from geographical scale effects, lower absolute transport demand, and regulatory environments that facilitate rapid policy implementation. These factors significantly reduce per-capita emissions and energy use.

Conversely, large and complex economies face inherently higher transport volumes even when vehicles and infrastructure are technologically efficient. These high volumes scale up total energy use and emissions, making it inherently more difficult to achieve favourable outcomes on absolute sustainability indicators without ambitious structural reforms. Research on global transport emissions confirms that high-income countries tend to register substantially higher transport emissions per capita compared with middle- and lower-income countries. To mitigate this scale and income bias, countries with similar policy effort but differing structural or demographic contexts are not misinterpreted as performing equally in sustainability outcomes.

6. Theoretical, practical and policy implications

6.1. Theoretical implications and alignment with existing literature

The results of the CRTSI strongly align with recent literature emphasizing that road transport sustainability is primarily driven by policy choices, governance structures, and sector-specific interventions, rather than by economic development alone. This finding is consistent with the growing consensus that transport decarbonization requires targeted and mode-specific strategies.

Several authors have highlighted the structural difficulty of decoupling transport growth from environmental impacts in the absence of strong public intervention. For instance, Creutzig et al. (2015, 2022) argue that transport emissions are particularly resistant to passive

decarbonization pathways and require integrated policy packages combining pricing instruments, technological change, and demand management. The strong performance of Nordic countries in the CRTSI reflects the effectiveness of such integrated approaches, particularly in road transport electrification and fiscal regulation.

Recent contributions further stress that economic efficiency and infrastructure quality alone are insufficient to achieve environmental sustainability. Schwanen et al. (2022a,b) and Anable et al. (2023a,b) demonstrate that high-income economies often experience rebound effects and freight growth that offset technological gains, especially in road transport. This supports the CRTSI finding that countries such as Germany and Poland, despite advanced transport systems, remain constrained by high freight volumes and fossil fuel dependence.

The critical role of road freight as a bottleneck in transport decarbonization is well documented. According to the International Transport Forum (ITF, 2023), road freight remains the fastest-growing source of transport emissions in many OECD countries, largely due to structural reliance on trucking and the limited effectiveness of modal shift policies. This finding directly echoes the CRTSI results, where freight transport volume and energy consumption are key drivers of lower sustainability rankings for large, transit-oriented economies.

Moreover, studies on socio-technical transitions and governance emphasize that successful sustainability outcomes depend on long-term policy coherence and institutional capacity. B.K. Sovacool et al. (2023) show that countries leading in low-carbon transport transitions combine regulatory pressure, financial incentives, and social acceptance, features strongly associated with the Nordic policy model identified in the CRTSI rankings.

At the global level, assessments by the Intergovernmental Panel on Climate Change (IPCC, 2022) reaffirm that transport sustainability pathways are highly context-dependent, and that early adopters of clean mobility policies achieve disproportionate benefits in emissions reduction and safety outcomes. The CRTSI empirically confirms this by showing that countries with early and aggressive intervention strategies consistently outperform late adopters, regardless of economic size.

Overall, the CRTSI contributes to the literature by operationalizing these theoretical insights into a transparent, road-transport-specific empirical framework. By isolating road transport sustainability, the index responds to recent calls (e.g., Banister, 2018; Schwanen et al., 2022a,b) to move beyond aggregate transport indicators and better capture the sectoral mechanisms driving environmental outcomes. In doing so, the CRTSI complements existing sustainability and competitiveness indices while offering new empirical evidence on the decisive role of policy-driven decoupling in road transport.

These findings indicate that road transport sustainability is driven more by policy interventions than by economic wealth alone, corroborating recent literature on decoupling. They empirically validate the theoretical emphasis on mode-specific policy tools, highlighting that conventional transport sustainability studies often underestimate the environmental burden of road freight. Furthermore, the CRTSI provides evidence that the Nordic model's success is replicable through targeted policy measures, offering a counterpoint to studies suggesting that geographic factors are the primary determinants of sustainability performance.

6.2. Policy, theoretical, and practical implications

The observation that Nordic countries consistently rank highest in the CRTSI provides strong empirical support for the hypothesis that successful decoupling of transport growth from environmental impact is primarily achievable through proactive policy interventions, such as carbon pricing and incentives for electric vehicles. This finding aligns with recent studies highlighting the effectiveness of stringent regulatory frameworks and targeted technological support in promoting sustainable transport outcomes.

Conversely, the relatively lower ranking of major economies such as Germany and Poland, despite their advanced transport infrastructure, challenges the conventional assumption that economic development alone ensures transport sustainability. This pattern underscores that structural characteristics and policy factors, rather than infrastructure quality per se, are critical determinants of sustainable transport performance, echoing concerns raised in the literature regarding the persistent challenges of decarbonizing freight and reducing transport-related emissions in industrialized contexts.

Overall, these results reinforce the importance of integrating policy-driven measures, technological innovation, and structural considerations in the pursuit of transport sustainability. They also contribute to the theoretical understanding of how cross-country heterogeneity in governance, policy intensity, and innovation capacity shapes observed sustainability outcomes.

At a practical level, the CRTSI serves as a robust decision-support tool for policymakers, enabling the identification of specific strengths and weaknesses in road transport sustainability. High-scoring countries can be benchmarked for best practices in areas such as road safety, fleet electrification, and low-emission vehicle adoption, while low-scoring countries are flagged for urgent implementation of targeted interventions, including road-specific carbon pricing, congestion charging, and incentives for modal shifts.

Key policy insights derived from the CRTSI include:

- Low-performing countries (e.g., Germany, Poland, Turkey) require urgent measures to reduce fossil fuel dependence through congestion pricing, low-emission zones, stricter freight decarbonization policies, and modal shift incentives.
- Mid-performing countries (e.g., Portugal, Greece, Tunisia) should focus on incremental improvements, including public transport expansion, fleet electrification, and integrated policy packages combining regulatory measures with financial incentives.
- High-performing countries (e.g., Iceland, Norway, Finland) provide transferable best practices, particularly in renewable energy integration, safety policies, demand management, and rapid implementation of decarbonization strategies.

Regular updates of the CRTSI allow policymakers to track progress over time, assess the effectiveness of interventions, and adapt strategies dynamically, thereby supporting long-term sustainability transitions in road transport. By linking theoretical insights with practical guidance, this integrated framework demonstrates how policy-driven decoupling, technological innovation, and structural considerations together determine road transport sustainability outcomes.

7. Conclusion

This study developed and validated the Composite Road Transport Sustainability Index (CRTSI), a robust, transparent, and road-transport-specific benchmarking tool for 32 countries over 2011–2021. The analysis reveals a clear three-tier sustainability structure, with Nordic countries leading due to policy-driven decoupling, Central European countries demonstrating moderate performance driven by wealth and efficiency, and intermediate countries like Tunisia highlighting opportunities for targeted policy improvements. Empirical results show that Iceland (0.980), Norway (0.920), and Finland (0.890) achieve the highest sustainability performance, whereas Turkey (0.228), Germany (0.347), and Poland (0.431) lag, largely due to high fossil fuel dependence, road freight dominance, and structural constraints.

The CRTSI addresses major gaps in the literature by providing a sector-specific, cross-country, and longitudinal assessment, overcoming limitations of existing indices that either conflate transport modes, are limited to single-year analyses, or offer limited policy relevance. Correlation analyses confirm strong interdependencies between economic development, energy consumption, freight volumes, and CO_2 emissions, highlighting the central role of freight transport and energy efficiency in

shaping sustainability outcomes.

Scientific Contributions:

- Conceptual: Establishes road transport sustainability as a distinct domain, allowing for more granular and actionable insights than broad multimodal indices. It identifies structural weaknesses and policy successes related to fleet management, road safety, and emissions, providing a policy-oriented interpretation.
- Methodological: Offers a transparent, reproducible PCA-based framework for constructing composite indices on panel data. Robustness is confirmed through sensitivity analyses using alternative normalization and weighting methods.
- Empirical: Demonstrates that leadership in transport sustainability is determined more by effective policy choices, including decarbonization strategies, EV incentives, and safety regulations, than by economic wealth alone.
- Practical: Provides policymakers with a clear, actionable performance metric to benchmark countries, monitor progress over time, and guide targeted interventions according to structural and policy-specific needs.

The research objectives are validated:

RQ1: Synthesizes the multidimensional concept of road transport sustainability into a single, objective metric.
RQ2: Reveals a three-tier structural pattern across countries and captures temporal trends.
RQ3: Identifies key policy and structural determinants, including decoupling, road safety, and freight volumes, which explain observed cross-country heterogeneity.

From a practical and policy perspective, the CRTSI not only benchmarks performance but also provides actionable insights, guiding countries toward sustainable, low-carbon, and inclusive road transport systems. By combining rigorous measurement with practical recommendations, it offers a clear roadmap for governments aiming to align transport policy with environmental and social objectives.

Several key insights emerge for policymaking. First, targeted policy interventions are essential. Countries in intermediate or low sustainability categories should strengthen their sustainable mobility strategies, implementing environmental and energy measures to reduce the carbon footprint. The continued reliance on fossil fuels remains a major barrier, emphasizing the need to accelerate the greening of vehicle fleets by promoting eco-friendly, safe, and accessible public transport, including electric buses. Similarly, the adoption of clean vehicles, electric and hybrid cars, should be incentivized through subsidies, tax reductions, and other supportive measures to make sustainable choices more attractive to users.

Second, improving data quality and monitoring is crucial for effective policy. Policymakers should invest in regular, disaggregated, and standardized data collection, covering regional and sectoral differences. Integrating tools such as Geographic Information Systems (GIS) can help identify areas requiring targeted interventions. Regular updates of the CRTSI provide the ability to track progress, evaluate intervention effectiveness, and adjust strategies dynamically.

Third, learning from best practices is vital. High-performing countries like Iceland, Norway, and Finland demonstrate exemplary road transport sustainability through integrated transport planning, renewable energy integration, and sustainable mobility incentives. Lessons from these countries can inform strategies in intermediate and low-performing nations, promoting technology transfer and replication of successful interventions.

Finally, regional collaboration and equity should guide policy design. Observed patterns show that Northern European countries consistently outperform Eastern European countries, highlighting the potential for regional cooperation, sharing best practices, and reducing disparities. Policies should also ensure equitable access to sustainable transport, particularly for rural and low-income populations, to avoid reinforcing mobility inequalities.

While the CRTSI offers a robust, transparent, and comparable metric for assessing road transport sustainability, it is not without limitations. The index currently excludes several important social and economic dimensions, including equity, congestion, modal split, and accessibility, due to the need for complete, harmonized panel data across all 32 countries from 2011 to 2021. This reflects a deliberate trade-off between methodological rigor and conceptual completeness, ensuring comparability and longitudinal consistency while acknowledging that certain aspects of transport sustainability remain underexplored.

Additionally, the CRTSI does not fully capture institutional, technological, and behavioural factors, such as governance frameworks, mobility habits, electrification, and innovation in sustainable mobility, that can significantly influence outcomes. Nor does it account for sub-national dynamics, as the analysis is conducted at the national level, potentially overlooking urban and regional variations that are critical for targeted policy interventions.

Future research can build upon these limitations by expanding the scope of indicators to include social, economic, institutional, behavioural, and technological dimensions. The integration of proxy variables, advanced imputation, or panel data techniques could allow researchers to maintain methodological consistency while enriching the conceptual coverage of the index. Applying the CRTSI at regional and urban scales, where more granular datasets are available, would further enhance its policy relevance and practical utility.

Moreover, continuous updating of the CRTSI would enable dynamic monitoring of transport sustainability, allowing policymakers to assess the effectiveness of interventions, adapt strategies, and track long-term progress toward low-carbon, safe, and efficient mobility. Improving the quality, granularity, and frequency of transport data, including disaggregated and GIS-integrated indicators, will be essential to target interventions effectively and provide actionable insights for decision-makers. Finally, it is recommended to adopt a multi-scale approach, assessing sustainability at local, regional, and national levels (city, region, country), and to expand the number of indicators to provide a more comprehensive and precise evaluation of transport sustainability.

In summary, while the CRTSI represents a significant step forward in road-transport-specific sustainability assessment, future extensions can make it more comprehensive, multi-dimensional, and locally relevant, further supporting evidence-based policy design and the global transition to sustainable, equitable, and low-carbon transport systems.

CRediT authorship contribution statement

Khaled Ben Abdallah: Writing – original draft, Methodology, Conceptualization. **Sabrine Khalifa:** Resources, Formal analysis.

Declarations of interest

None.

Data availability

Data will be made available on request.

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