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The LESG Index: A Data-Driven Composite Framework for Assessing Systemic Supply Chain Readiness through Logistics and ESG Performance

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Featured Application

The LESG index serves as a data-driven benchmarking tool for assessing national readiness for resilient and sustainable supply chain systems, supporting policy design and investment prioritization in logistics infrastructure, governance, and sustainability integration.

Abstract

This study introduces the LESG index as a composite measure of national systemic readiness for sustainable development, integrating logistics performance, governance quality, and sustainability outcomes within a unified data-driven analytical framework. Moving beyond outcome-oriented approaches based primarily on income metrics, the framework conceptualizes development as a structural condition emerging from the coherence of interdependent dimensions that also condition the effectiveness of digitally enabled supply chain systems. Using cross-country data for 123 countries, the index is constructed through normalization procedures and Principal Component Analysis, and externally validated against GDP per capita within a diagnostic, non-causal framework. Cluster analysis is subsequently employed to identify distinct systemic development readiness regimes. The results reveal substantial cross-country heterogeneity that remains obscured in income-based or single-indicator assessments, highlighting coherent structural configurations of logistics capability, institutional quality, and sustainability alignment. These regimes differentiate countries beyond conventional development classifications and provide insight into varying readiness conditions for resilient and sustainable logistics and supply chain environments. Overall, the LESG index functions as a transparent diagnostic tool for comparative analysis and policy interpretation, reframing development in terms of systemic readiness rather than ex post economic performance and offering a macro-structural perspective relevant to data-driven and digital supply chain transformation.

Keywords: systemic readiness; logistics performance; digital supply chains; composite indicators; sustainability alignment; data-driven modeling; governance quality; resilience

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1. Introduction

The measurement of economic development has traditionally relied on aggregate macroeconomic indicators, most notably Gross Domestic Product (GDP). Despite its analytical convenience, GDP has long been recognized as an incomplete representation of development, capturing economic output while abstracting from social welfare, environmental sustainability, and institutional conditions. From its earliest conceptualization, GDP was understood as an approximation—a synthesis of heterogeneous and imperfect measurements—rather than a comprehensive diagnostic of economic reality [1]. Subsequent research has reinforced this critique, highlighting that GDP provides only a partial and potentially misleading account of national development trajectories, particularly when used in cross-country comparisons [2–4]. As a result, GDP primarily reflects ex post economic outcomes, offering limited insight into the underlying structural conditions that enable countries to sustain development over time. However, the limitation of GDP is not merely that it omits sustainability or institutions, but that it captures development ex post, offering little insight into the structural conditions that enable economies to sustain development over time.

In response to these limitations, the literature has expanded to include complementary indicators addressing specific dimensions of development, such as governance quality, environmental performance, and social outcomes. While this proliferation has enriched empirical analysis, it has also produced a fragmented indicator landscape in which development is assessed through parallel, weakly connected dimensions rather than as a coherent systemic process. As a result, development is frequently assessed through isolated dimensions rather than as a systemic process emerging from the coherence among economic structures, institutions, and sustainability policies. The central challenge, therefore, is no longer merely to expand the set of indicators, but to develop integrative approaches that can meaningfully synthesize multiple dimensions of development into analytically coherent constructs, while remaining transparent about the inherent subjectivity of macroeconomic measurement.

Within this broader debate, national logistics performance has gained prominence as a critical enabler of economic activity and integration into global value chains. Efficient logistics systems reduce transaction costs, facilitate trade, and enhance productive capacity, thereby shaping development outcomes. The Logistics Performance Index (LPI) has become a widely used benchmark for capturing these capabilities through expert-based assessments of logistics efficiency [5]. However, logistics performance does not operate independently. Its developmental impact depends fundamentally on the institutional environment in which it is embedded, including regulatory quality, governance effectiveness, and political stability, while sustainability considerations—environmental protection, social inclusion, and long-term resource management—have become integral to contemporary development strategies. These dimensions—logistics, institutions, and sustainability—form an interdependent system characterized by dynamic interactions rather than linear causality, suggesting that development capacity is better understood as a systemic property arising from their alignment rather than as the sum of independent indicators.

This fragmentation gives rise to a clear research gap: despite extensive empirical evidence on the importance of logistics performance, institutional quality, and sustainability outcomes, there is no widely accepted composite metric that explicitly integrates these dimensions into a unified analytical framework capable of capturing a country's systemic readiness for sustainable development. Existing composite indices tend to emphasize either economic competitiveness or sustainability outcomes, while logistics-oriented metrics focus on operational efficiency without incorporating governance and environmental constraints.

Against this background, this study addresses the following research question: How can national systemic readiness for sustainable development be meaningfully measured through an integrated analytical framework that jointly accounts for logistics performance, institutional quality, and sustainability outcomes? To address this question, the study conceptualizes development readiness as a structural condition rather than an ex post economic outcome and introduces the LESG index as a composite diagnostic tool for cross-country analysis. The analysis shows that logistics performance, governance quality, and sustainability outcomes form coherent structural configurations that differentiate countries beyond income-based classifications, revealing distinct development readiness regimes that remain obscured when these dimensions are examined in isolation.

Building on recent work that reconceptualizes development as a multidimensional and systemic process shaped by logistics performance and ESG conditions [6], the present study advances this perspective by introducing the LESG Index (Logistics–Environmental, Social and Governance Index) as a composite measure of national systemic readiness for sustainable development. Rather than replacing established indicators such as GDP or the Logistics Performance Index, or functioning as a direct measure of economic outcomes, the LESG index is designed to capture the coherence among logistics capability, institutional quality, and sustainability performance as a structural condition enabling sustainable development trajectories within a unified analytical framework.

It is important to clarify that the LESG index is not designed as a measure of development outcomes, nor as a substitute for income-based indicators. Instead, it operationalizes systemic readiness as a structural condition reflecting the coherence of logistics capability, institutional quality, and sustainability alignment. As such, LESG is explicitly diagnostic rather than predictive, and its purpose is to structure cross-country comparison under conditions of unavoidable measurement subjectivity. The LESG index is not designed to predict economic growth, establish causal relationships, or replace income-based indicators. Instead, it functions as a diagnostic measure of systemic readiness, capturing the structural alignment of logistics capability, institutional quality, and sustainability performance. Beyond its macro-level relevance, systemic readiness is expected to shape the behavioral environment in which economic agents operate. By influencing institutional trust, information transparency, and sustainability norms, national readiness conditions may indirectly affect both firms' strategic incentives and profitability prospects as well as consumers' expectations, preferences, and responses to sustainability-related signals, particularly in digitally mediated market contexts.

The study makes three main contributions to the literature. First, it offers a conceptual contribution by reframing development capacity as a systemic property arising from the coherence of infrastructure, institutions, and sustainability policies, rather than as the outcome of isolated achievements in individual domains. By emphasizing readiness and structural alignment over ex post performance, this perspective advances the development literature toward a more integrative understanding of national development capacity.

Second, the study provides a methodological contribution through the transparent construction of a composite index grounded in multivariate statistical analysis. The use of Principal Component Analysis (PCA) and variance-based weighting minimizes arbitrary normative choices while explicitly acknowledging the inherent subjectivity of composite indicator design, in line with established international guidelines [7].

Third, the study delivers an empirical contribution by validating the LESG index against GDP per capita and by employing cluster analysis to identify distinct systemic development regimes among countries. This classification reveals heterogeneity in development readiness that remains obscured in conventional indicators, thereby enhancing the diagnostic and policy relevance of the proposed framework. Taken together, these contributions motivate a clear and focused analytical question regarding how such systemic readiness can be meaningfully operationalized.

Beyond its macro-development orientation, the LESG framework can be interpreted as a data-driven systemic modeling layer that conditions the digital transformation of supply chains. Contemporary Digital Supply Chains (DSCs) rely on advanced technologies—including cloud computing, AI-enabled analytics, IoT-based traceability, and data-sharing infrastructures—to enhance resilience, sustainability, and operational transparency. However, the effective deployment of such technologies depends on broader structural preconditions, including logistics capability, governance reliability, and sustainability alignment. At the enterprises-operational level, empirical evidence further demonstrates that digital transformation improves supply chain competitive performance primarily through the strengthening of organizational capabilities—such as information exchange, activity integration, coordination, and responsiveness—indicating that digital technologies generate value only when embedded within supportive structural and institutional conditions [8]. In this context, the LESG index provides a holistic, multivariate readiness model that

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captures the macro-structural environment within which data-driven supply chain engineering solutions are implemented. By identifying coherent systemic configurations, the framework contributes to understanding how national-level readiness shapes the feasibility, stability, and long-term effectiveness of digital and AI-enabled supply chain systems.

The remainder of the article is structured as follows. Section 2 develops the conceptual framework. Section 3 outlines the methodological framework of the study, describing the data sources, indicator selection, normalization procedures, and the analytical steps involved in constructing the LESG index. Section 4 presents the empirical results, including the validation of the LESG index through regression analysis and the identification of systemic development readiness patterns. Section 5 discusses the findings in relation to the broader literature on development, logistics performance, and sustainability, and highlights their analytical and policy implications. Finally, Section 6 concludes by summarizing the main contributions of the study, acknowledging its limitations, and outlining directions for future research. Detailed statistical results and supplementary empirical material are reported in the Appendices to ensure transparency and replicability.

2. Conceptual Framework

2.1. Composite Indicators and Subjectivity

The measurement of economic development has historically relied on aggregate macroeconomic indicators, with Gross Domestic Product (GDP) occupying a dominant position. From its earliest formulation, however, GDP was acknowledged as an imperfect approximation rather than a comprehensive representation of economic and social well-being. Kuznets [1] explicitly emphasized that national income statistics combine precise measurement with estimation and judgment, cautioning against their interpretation as direct indicators of welfare. Subsequent literature has reinforced this critique by highlighting the conceptual and empirical limitations of GDP, including its insensitivity to distributional outcomes, social welfare, and environmental externalities [2] as well as the normative assumptions embedded even in ostensibly objective welfare measures [9]. These challenges are amplified in international comparisons, where purchasing power parity adjustments, imputation procedures, and data gaps introduce additional layers of subjectivity, particularly in non-market sectors and developing economies [10,11]. Importantly, this body of work does not negate the analytical value of GDP but instead delineates its epistemic boundaries and underscores the need for complementary indicators capable of capturing structural and qualitative dimensions of development [12].

Parallel concerns arise in the measurement of logistics performance, a dimension widely recognized as critical for economic growth, trade competitiveness, and participation in global value chains [13–15]. Empirical studies consistently demonstrate that improvements in logistics efficiency reduce trade costs, enhance export performance, and support economic specialization [16–18]. At the same time, logistics performance is inherently multidimensional, encompassing infrastructure quality, institutional effectiveness, service reliability, and regulatory coordination. The Logistics Performance Index (LPI) has therefore emerged as a widely used benchmark, yet its reliance on expert assessments introduces perceptual subjectivity into cross-country comparisons. Stepanova [19] highlights that expert judgments may vary systematically across countries and development levels. Nevertheless, perception-based measures remain analytically valuable, as logistics performance cannot be fully captured through physical or administrative data alone; public investment choices, regulatory frameworks, and institutional coordination play a decisive role in shaping logistics outcomes [20,21].

Taken together, the limitations of GDP and logistics indicators point to a broader methodological insight: subjectivity is an inherent and unavoidable feature of development measurement. Economic and infrastructural indicators necessarily involve aggregation across heterogeneous activities, sectors, and institutional arrangements, embedding methodological conventions and normative priorities in the measurement process. This insight is reinforced by studies linking logistics performance to economic growth through complex and context-dependent mediating channels, such as foreign direct investment and trade facilitation [22–24]. Treating any single indicator as an objective benchmark therefore risks obscuring systemic interactions and overstating measurement precision. Rather than attempting to eliminate subjectivity, the literature increasingly emphasizes the importance of structuring it transparently, as subjectivity becomes problematic only when it remains implicit, unacknowledged, or methodologically inconsistent [9].

2.2. Composite Indicators as Structured Aggregation

Composite indicators provide a methodological response to the challenge of measuring complex development processes under conditions of inevitable subjectivity. By aggregating multiple dimensions within a single analytical framework, composite indices allow researchers to synthesize information while maintaining transparency regarding underlying assumptions.

In the context of logistics and development, composite approaches have been shown to outperform single-indicator analyses in capturing systemic effects. High-quality logistics services facilitate trade by reducing time and uncertainty, but their impact depends on institutional quality and complementary public investment [25]. Composite indicators are particularly well suited to capturing such interactions, as they allow multiple dimensions to be evaluated jointly rather than sequentially.

Crucially, the value of composite indicators lies not in claims of objectivity but in their capacity to impose analytical structure on multidimensional phenomena. When constructed transparently, they function as diagnostic tools that reveal patterns of coherence and imbalance across development dimensions.

A central conceptual distinction in this study is between economic outcomes and systemic readiness. Indicators such as income levels or export volumes primarily reflect past performance, whereas systemic readiness refers to the structural capacity of an economy to sustain development over time. This capacity depends on the alignment of logistics infrastructure, institutional quality, and trade facilitation mechanisms. Empirical research shows that disruptions in logistics systems can generate economy-wide effects even in advanced economies [26], while sustained improvements in logistics performance contribute to long-term competitiveness only when embedded within supportive institutional and policy environments [14,25]. These findings support a systemic interpretation of development, in which readiness emerges from the coherence of multiple structural components rather than from isolated improvements in individual domains.

Within this framework, the LESG index is positioned as a composite measure designed to capture national systemic readiness for sustainable development. By integrating logistics performance with governance quality and sustainability-related dimensions, the index reflects the literature's recognition that development is inherently multidimensional and interdependent. The LESG index is not intended to replace established indicators such as GDP or logistics-specific metrics, nor to establish causal relationships between its components and economic outcomes. Instead, it provides a structured analytical lens through which the coherence of development-relevant dimensions can be assessed and compared across countries. In doing so, it responds directly to long-standing concerns regarding the subjectivity and fragmentation of development measurement by offering a transparent and integrative composite framework. This distinction provides the conceptual foundation for interpreting composite indices as diagnostic tools rather than as outcome measures.

2.3. Systemic Readiness and Digital Supply Chain Transformation

Beyond their statistical construction, composite indicators increasingly serve as structural modeling tools for understanding complex transformation processes within interconnected socio-technical systems.

In this context, the digital transformation of supply chains has accelerated under the Industry 4.0 and Industry 5.0 paradigms, where advanced technologies such as artificial intelligence (AI), Internet of Things (IoT) infrastructures, blockchain-based traceability systems, and cloud-enabled analytics are increasingly deployed to enhance resilience, sustainability, and operational transparency. Systematic reviews indicate that AI-enabled decision systems and digital integration mechanisms significantly improve supply chain visibility, coordination, and sustainability performance [27,28].

Empirical evidence further suggests that digital supply chain (DSC) adoption is positively associated with improvements in resilience capabilities and sustainability outcomes, particularly in disruption-prone environments [29,30]. Digital transformation enhances adaptability and risk mitigation across interconnected supply chain networks by strengthening information flows and real-time monitoring capacities [31].

However, the literature also emphasizes that technological deployment alone does not guarantee systemic transformation. The effective implementation of Industry 4.0 infrastructures depends on broader structural and institutional conditions, including logistics capability, governance reliability, interoperability standards, and regulatory coherence [32,33]. Digital maturity is therefore embedded within a wider socio-economic and institutional ecosystem that conditions long-term performance outcomes [34].

In sustainability-oriented supply chains, IoT-enabled monitoring systems and data-driven analytics require stable infrastructure and coordinated governance mechanisms to produce measurable gains [35]. Recent conceptual work further highlights that digital technologies operate as enabling mechanisms within broader transformative supply chain architectures [36].

Within this perspective, the LESG framework can be interpreted as a data-driven systemic readiness model capturing the macro-structural conditions under which digital supply chain engineering solutions are deployed. By integrating logistics capability, governance quality, and sustainability performance into a unified multivariate construct, the LESG index complements technology-centered approaches by identifying structural coherence and institutional maturity. Rather than modeling digital technologies directly, the framework provides an analytical readiness layer that conditions the feasibility, stability, and long-term effectiveness of AI-enabled, IoT-integrated, and blockchain-supported supply chain systems.

3. Methodology

3.1. Data Sources and Indicator Selection

Four composite indices were selected to represent the core dimensions of the LESG framework. National logistics capability is proxied by the Logistics Performance Index (LPI) developed by the World Bank, which captures countries' integration into global value chains through expert-based assessments of customs efficiency, infrastructure quality, logistics services, shipment arrangements, tracking and tracing, and timeliness. LPI scores range from 1 (low performance) to 5 (high performance) and have been widely used in empirical studies on trade facilitation and logistics efficiency, forming the logistics pillar of the LESG index [37].

Environmental sustainability is represented by the Environmental Performance Index (EPI), jointly developed by Yale and Columbia Universities [38]. The EPI aggregates indicators related to environmental health, ecosystem vitality, and climate change mitigation into a normalized scale ranging from 0 to 100, capturing the environmental alignment of national development pathways.

The social and long-term development dimension is captured by the Sustainable Development Goals (SDG) Index, which aggregates indicators across economic, social, environmental, and institutional domains to assess countries' progress toward the 2030 Agenda, producing composite scores between 0 and 100 [39].

Institutional quality is measured using the Worldwide Governance Indicators (WGI) produced by the World Bank, covering six governance dimensions: Voice and Accountability, Political Stability, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption [40]. To reduce dimensional complexity and multicollinearity, a composite governance measure was constructed as the arithmetic mean of the six indicators, following established practice. This composite measure constitutes the governance pillar of the LESG index. Throughout the analysis, institutional quality and governance are treated as analytically equivalent concepts, reflecting the effectiveness and reliability of formal institutions shaping economic and sustainability outcomes.

The empirical analysis is conducted on a balanced cross-sectional sample of 123 countries, selected based on the availability of complete and consistent data across all four indices. Although reference years differ slightly due to publication cycles, the most recent available observations were used in all cases. This approach is consistent with prior cross-country research and does not compromise comparability, as the selected indicators capture relatively stable structural characteristics rather than short-term fluctuations. Detailed information on variables, sources, and descriptive statistics is provided in Appendix A.

3.2. Data Preparation, Normalization, and Suitability for Multivariate Analysis

Because the selected indicators are reported on different numerical scales, a harmonization process was applied prior to multivariate analysis and aggregation. Indicators originally reported on a 0–100 scale (Environmental Performance Index and SDG Index) were retained without transformation, while Logistics Performance Index scores (1–5 scale) and Worldwide Governance Indicators (−2.5 to +2.5 scale) were linearly rescaled to a common 0–100 range. This procedure preserves the relative ranking of countries within each indicator while ensuring comparability across dimensions.

GDP per capita, used subsequently for external validation, exhibits a highly skewed distribution and was therefore log-transformed prior to normalization. Distributional diagnostics, including Shapiro–Wilk tests and visual inspections, indicate that deviations from normality persist for several variables even after transformation. These diagnostics motivate the complementary use of parametric and non-parametric techniques in subsequent analyses and are reported in detail in Appendix A. Importantly, the normalization procedure does not impose distributional assumptions but facilitates consistent multivariate analysis across heterogeneous indicators.

Before proceeding to index construction, the suitability of the normalized dataset for multivariate analysis was formally assessed using standard diagnostic tests. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were employed to evaluate whether the correlation structure among variables justified the application of factor-based techniques. The results of both diagnostics confirm that the dataset exhibits sufficient intercorrelation and dimensional coherence to support dimensional reduction and component extraction. These findings provide the methodological justification for employing Principal Component Analysis (PCA) as the core technique for constructing the LESG index. Detailed diagnostic statistics are reported in Appendix B.

Linear rescaling was preferred over standardization techniques such as z-scores in order to preserve the intuitive interpretation of indicator distances while avoiding distortions arising from extreme values.

3.3. Principal Component Analysis and Index Construction

The methodological objective of the LESG framework is diagnostic rather than causal. The index is designed to capture systemic readiness for sustainable development by identifying structural coherence among logistics, governance, and sustainability dimensions, in line with the conceptual distinction between development readiness and observed economic outcomes.

Principal Component Analysis (PCA) is employed as the core technique for dimensionality reduction and composite index construction. PCA is appropriate in this context because the selected indicators are correlated and jointly reflect latent structural dimensions underlying development readiness. The suitability of the dataset for factor-based analysis is assessed using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity, which confirm the appropriateness of applying PCA.

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Component extraction follows the Kaiser criterion (eigenvalues greater than one) and is supported by inspection of the scree plot. An orthogonal Varimax rotation is applied to enhance interpretability while preserving statistical independence among components. PCA is used exclusively as a data-reduction and weighting mechanism, without imposing a priori assumptions regarding the relative importance of individual dimensions.

Weights for the LESG index are derived from the proportion of variance explained by the retained principal components, following a variance-based weighting approach consistent with established guidelines on composite indicator construction. The final LESG score is computed as a weighted linear combination of the extracted components, with higher values indicating greater systemic readiness for sustainable development. Detailed PCA diagnostics, including factor loadings, communalities, eigenvalues, and explained variance, are reported in Appendix B. This variance-based weighting scheme does not imply normative importance but reflects the empirical contribution of each component to the underlying variance structure of the data.

3.4. Empirical Validation Through Regression Analysis

To assess the empirical relevance of the LESG index, external validation is conducted using GDP per capita as a benchmark outcome indicator. This validation is explicitly diagnostic rather than causal. Ordinary Least Squares (OLS) regression is employed within a parsimonious cross-sectional framework, with normalized GDP per capita specified as the dependent variable and the LESG index as the explanatory variable.

Standard diagnostic checks, including multicollinearity assessment, residual analysis, and influence diagnostics, are conducted to ensure statistical adequacy and robustness. Regression estimates are interpreted as indicative of coherence between systemic readiness and observed economic performance rather than as evidence of causal effects. Full regression outputs and diagnostic statistics are reported in Appendix C.

Potential concerns related to endogeneity and reverse causality are acknowledged; however, given the diagnostic purpose of the analysis, the regression is not interpreted causally but as an external consistency check.

3.5. Cluster Analysis and Regime Identification

To explore structural heterogeneity beyond bivariate association, cluster analysis is employed to identify groups of countries with similar systemic readiness profiles. A two-stage clustering approach is adopted to balance exploratory insight with statistical robustness. In the first stage, hierarchical clustering is used to examine the underlying structure of the data and to inform the selection of an appropriate number of clusters based on dendrogram inspection and the agglomeration schedule.

In the second stage, k-means clustering is applied to refine cluster membership and improve within-cluster homogeneity. Clustering is performed on standardized LESG index values to ensure comparability across observations and to avoid scale-driven distortions. This combined approach allows for consistent classification while preserving interpretability and stability of the resulting cluster solutions.

Cluster centroids reported in Table D2 (Appendix D) correspond to the final cluster centers produced by the k-means algorithm applied to standardized LESG scores. These centroids represent the mean position of each cluster in the multivariate space and serve as reference points for cluster interpretation. Cluster membership is assigned based on minimum Euclidean distance to these centroids rather than on predefined threshold values.

The cluster analysis is designed as a diagnostic tool to identify distinct systemic development regimes reflecting different configurations of logistics capability, institutional quality, and sustainability performance, rather than as a ranking mechanism. Detailed clustering diagnostics, validation tests, and robustness checks are reported in Appendix D.

This regime-based classification facilitates interpretation by shifting the analytical focus from marginal score differences to structurally distinct patterns of development readiness.

3.6. Transparency, Robustness and Limitations

The cross-sectional design adopted in this study is a deliberate methodological choice rather than a constraint. Since the LESG index is intended to capture structural readiness rather than dynamic adjustment processes, temporal variation is not required for its conceptual validity. Longitudinal extensions are therefore viewed as complementary rather than necessary for the present diagnostic purpose.

To preserve analytical clarity in the main text while ensuring transparency and replicability, detailed statistical outputs, robustness checks, and supplementary analyses are reported in the Appendices. These include extended descriptive statistics and normality diagnostics (Appendix A), PCA diagnostics and component structures (Appendix B), regression results and residual diagnostics (Appendix C), clustering diagnostics and validation tests (Appendix D), and additional robustness checks, including alternative normalization and weighting schemes (Appendix E).

The empirical strategy adopted in this study is subject to several limitations that should be acknowledged. First, the cross-sectional design precludes the analysis of dynamic relationships, temporal adjustment processes, or causal effects. Second, GDP per capita, even when normalized and log-transformed, remains an imperfect benchmark for development outcomes, as it does not capture distributional aspects, social welfare, or environmental externalities. Third, several components of the LESG framework—most notably logistics performance and governance quality—are partially based on perception-based indicators, which may introduce measurement noise and cross-country comparability biases. Fourth, the construction of a composite index necessarily involves methodological choices regarding normalization, aggregation, and weighting, which, despite being structured and transparent, remain subject to alternative specifications. Finally, differences in data collection cycles across the underlying indices may introduce minor temporal inconsistencies, although these indicators are intended to capture relatively stable structural characteristics rather than short-term fluctuations.

These limitations do not undermine the analytical value of the LESG index but instead clarify its intended scope and interpretation. The LESG framework is not designed to replace outcome-based development indicators or to establish causal relationships; rather, it serves as a complementary diagnostic tool that captures the structural readiness underlying sustainable development trajectories.

4. Results

4.1. Principal Component Analysis

The PCA results indicate the presence of two dominant components that together explain 85,64% of the total variance in the dataset (see Appendix B, Tables B4-B5). The first component loads primarily on logistics-related indicators, reflecting national logistics capability and operational efficiency, while the second component loads predominantly on governance, environmental, and social indicators, capturing the institutional and sustainability dimension of development readiness.

This component structure is conceptually coherent and aligns with the systemic framework developed in Section 2. Rather than treating logistics, governance, and sustainability as independent pillars, the PCA reveals their organization into broader latent dimensions that jointly characterize national development readiness. The scree plot further confirms the concentration of variance in the first two components, supporting the retained component structure (Figure 1).

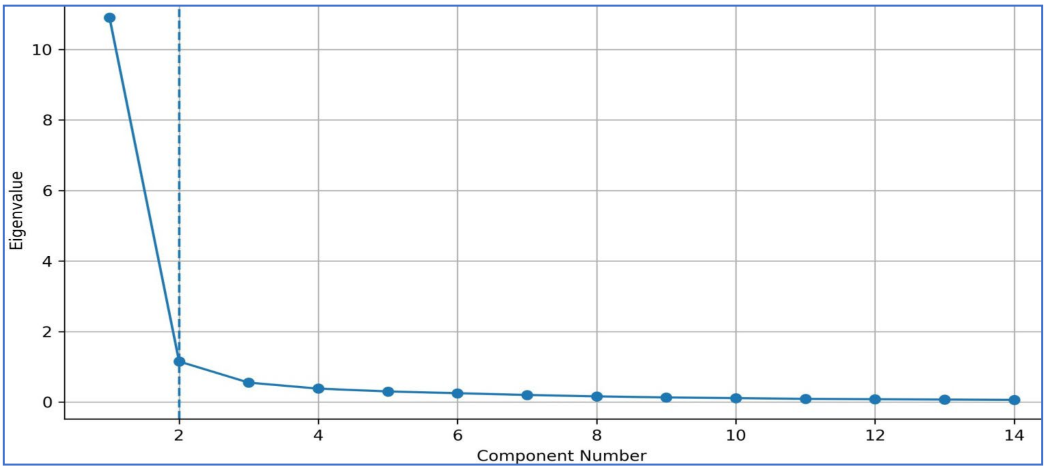

Figure 1. Scree plot of Principal Components.

Following component extraction, weights were assigned to each component based on the proportion of total variance explained, adopting a variance-based weighting scheme that reflects their relative contribution to the overall information content of the dataset. The final LESG index was constructed as a weighted linear combination of the extracted components, ensuring that both the logistics capability dimension and the institutional–sustainability dimension are represented in proportion to their empirical significance. Full PCA diagnostics, including eigenvalues, variance explained, and factor loadings, are reported in Appendix B. For transparency and replicability, normalized country-level LESG scores are reported in Table B6.

While the baseline PCA identifies two dominant components for index construction, robustness checks (Appendix E.2) indicate that these dimensions collapse into a single latent factor, reinforcing the interpretation of LESG as a unified readiness construct. Although robustness tests indicate the presence of a dominant latent structure, the two-component solution is retained in the baseline specification to preserve interpretability and to reflect the conceptually distinct but empirically related logistics and institutional–sustainability dimensions of systemic readiness.

4.2. Regression Analysis

The LESG index is conceptualized as a measure of systemic readiness for sustainable development rather than as an outcome indicator or a growth model. Nevertheless, external validation is necessary to assess whether the structural conditions captured by the index are meaningfully aligned with observable development outcomes. In this context, validation is explicitly diagnostic rather than causal and aims to examine the degree of association between systemic readiness and commonly used indicators of economic performance.

Regression analysis confirms this pattern. The Pearson correlation coefficient between LESG and GDP per capita is R = 0,886, indicating a strong linear association. The corresponding coefficient of determination (R^2 = 0,785) suggests that approximately 78,5% of the cross-country variation in normalized GDP per capita is statistically associated with differences in systemic readiness as captured by the LESG index. The estimated regression coefficient on LESG is positive and statistically significant at conventional confidence levels, and the overall model F-statistic strongly rejects the null hypothesis of no association. The regression diagnostics further support the statistical adequacy of the validation exercise. The Durbin–Watson statistic (DW = 2,043) is close to the benchmark value of 2, indicating no evidence of first-order autocorrelation in the residuals, which is consistent with the cross-sectional nature of the data (see Appendix C, Table C1).

The overall model is highly statistically significant. The ANOVA F-statistic (F = 440,830, $p <$ 0,001) strongly rejects the null hypothesis that the model explains no variation in the dependent variable, confirming the presence of a systematic linear association between the LESG index and normalized GDP per capita(see Appendix C, Table C2) .

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Consistent with these results, the standardized regression coefficient for the LESG index is large and positive (β = 0,886, p < 0,001), indicating that higher levels of systemic readiness are strongly associated with higher income levels in standardized terms (see Appendix C, Table C3). This coefficient mirrors the Pearson correlation coefficient, as expected in a single-regressor framework, and reinforces the interpretation of the regression as a diagnostic validation rather than a causal model.

Standard diagnostic checks support the adequacy of the regression specification. Variance Inflation Factor (VIF) values equal to unity confirm the absence of multicollinearity, while residual diagnostics do not indicate systematic deviations from normality or the presence of influential outliers. Full regression results and diagnostic statistics are reported in Appendix C.

Figure 2 visualizes the relationship between the LESG index (x-axis) and normalized GDP per capita (y-axis) for the 123-country sample. The scatter plot reveals a clear positive association: countries with higher systemic readiness, as captured by the integrated logistics–governance–sustainability framework, tend to exhibit higher normalized income levels. This visual evidence is presented strictly as diagnostic validation rather than as proof of causal effects.

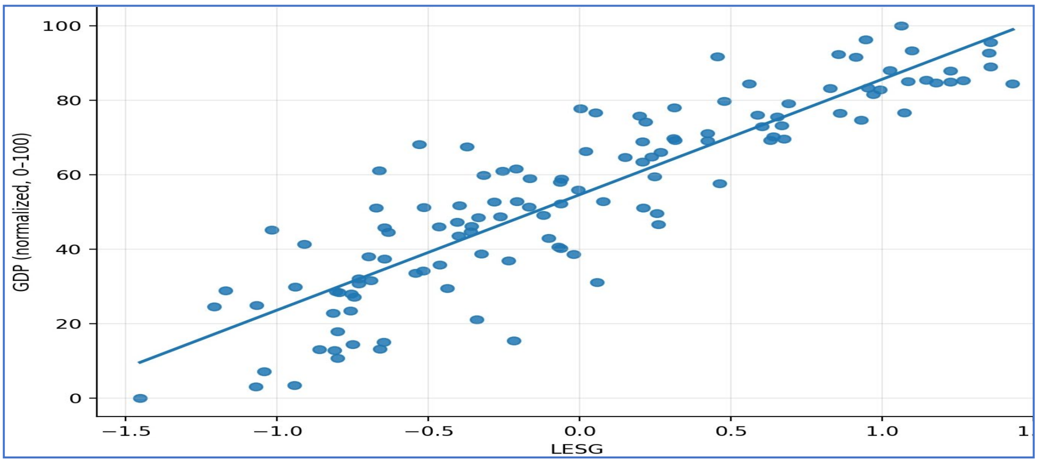

Figure 2. GDP (normalized) vs. LESG.

Importantly, the strong association observed between LESG and GDP per capita should not be interpreted as evidence of causality. The components of systemic readiness—logistics performance, governance quality, and sustainability outcomes—are jointly shaped by long-term economic development, institutional persistence, and historical path dependence. Accordingly, the results presented in this section are interpreted solely as validation of the index's empirical relevance. The LESG index effectively differentiates between countries with structurally favorable and unfavorable development conditions, supporting its use as a diagnostic and comparative tool.

Additionally, the strong association between LESG and GDP per capita does not imply that the index reproduces income rankings. GDP is not included in the construction of the LESG index, nor does it influence component extraction or weighting. Importantly, the high explanatory power should not be interpreted as circularity, as GDP is not included in the construction of the LESG index and does not influence component extraction or weighting; rather, the association reflects long-term structural co-evolution between income levels and systemic readiness conditions.

Moreover, the subsequent regime-based cluster analysis demonstrates that countries with comparable income levels may occupy distinct systemic readiness regimes, underscoring that LESG captures structural coherence rather than income performance. The magnitude of this association reflects the long-run co-evolution of logistics capability, institutional quality, sustainability outcomes, and income levels rather than a mechanical replication of GDP rankings within the LESG framework.

4.3. Cluster Analysis

The objective of the cluster analysis is not to refine country rankings or to impose threshold-based classifications, but to identify qualitatively distinct systemic configurations. Accordingly, the resulting regimes should be interpreted as diagnostic archetypes rather than as linear development stages or normative benchmarks.

While the empirical validation in Section 4.2 demonstrates a strong association between the LESG index and economic outcomes, bivariate relationships alone do not capture the structural heterogeneity of national development pathways. Countries with similar income levels may differ substantially in logistics capacity, institutional quality, and sustainability performance, while countries with comparable systemic readiness profiles may exhibit divergent income outcomes due to historical, geopolitical, or policy-specific factors.

To address this heterogeneity, cluster analysis is employed as a complementary diagnostic tool. The objective is not to rank countries, but to identify systemic development regimes—groups of countries that share similar structural configurations across the LESG dimensions. This regime-based classification enhances the analytical value of the LESG framework by revealing patterns that remain obscured in regression-based or income-centered analyses.

The clustering procedure identifies four distinct systemic development regimes, characterized by different configurations of logistics capability, governance quality, and sustainability performance (see Appendix D). Cluster labels were assigned ex post based on the relative position of cluster centroids along the LESG index. Since k-means cluster numbering is arbitrary, clusters were ordered from lowest to highest systemic readiness and subsequently interpreted as distinct systemic development regimes. This interpretation is grounded in the comparative magnitude of cluster centroids and aligned with the conceptual framework distinguishing vulnerable, transitional, moderate, and leading systemic configurations.

Four distinct regimes emerge. Cluster 1, exhibiting the lowest (negative) centroid, was interpreted as systemically vulnerable economies, while Cluster 4, characterized by less negative values, was classified as transitional systems. Cluster 2 reflects moderate performers with positive but intermediate systemic readiness, whereas Cluster 3, exhibiting the highest positive centroid, was identified as systemic leaders. Cluster labels are descriptive and heuristic, intended to facilitate interpretation of structural configurations rather than to convey normative judgments. The country composition of each cluster is reported in Appendix D (Tables D5–D8), which detail the countries included in each systemic development readiness regime. Cluster numbering follows the k-means output and is not ordinal; interpretive labels are assigned ex post based on centroid magnitude.

Systemically Vulnerable Economies are characterized by persistently low LESG scores across all dimensions. Weak logistics infrastructure, limited institutional capacity, and underdeveloped sustainability frameworks jointly constrain development readiness, leaving these economies highly exposed to external shocks and structural volatility (Table D5).

Transitional Systems exhibit intermediate LESG scores, typically reflecting improvements in one or two dimensions—such as logistics infrastructure or governance reforms—while lagging in others. These economies display signs of structural transition but lack the coherence required for sustained development readiness (Table D6).

Moderate Performers achieve relatively balanced performance across LESG dimensions without excelling in any single area. Logistics and institutional capacity support stable economic activity, yet sustainability integration remains uneven, constraining further upgrading toward more resilient and higher value-added development trajectories (Table D7).

Systemic Leaders record consistently high LESG scores across all dimensions. Strong logistics systems, high-quality institutions, and advanced sustainability frameworks reinforce one another, generating robust and resilient conditions for long-term development. While income levels in this group are generally high, their defining characteristic is structural coherence rather than income per se (Table D8).

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Figure 3 depicts the classification of countries into systemic development regimes by plotting the LESG index against normalized GDP per capita and differentiating observations according to k-means cluster membership. The figure illustrates that countries with similar income levels may exhibit markedly different levels of systemic readiness for sustainable development. Overall, Figure 3 underscores that development readiness is not reducible to income alone. The distribution of countries across regimes demonstrates the added diagnostic value of the LESG framework in identifying structural heterogeneity that remains obscured in income-based classifications. Cluster boundaries reflect relative positioning within the overall distribution of systemic readiness rather than absolute score thresholds, implying that countries with relatively high LESG values may still belong to intermediate regimes when structural coherence remains incomplete.

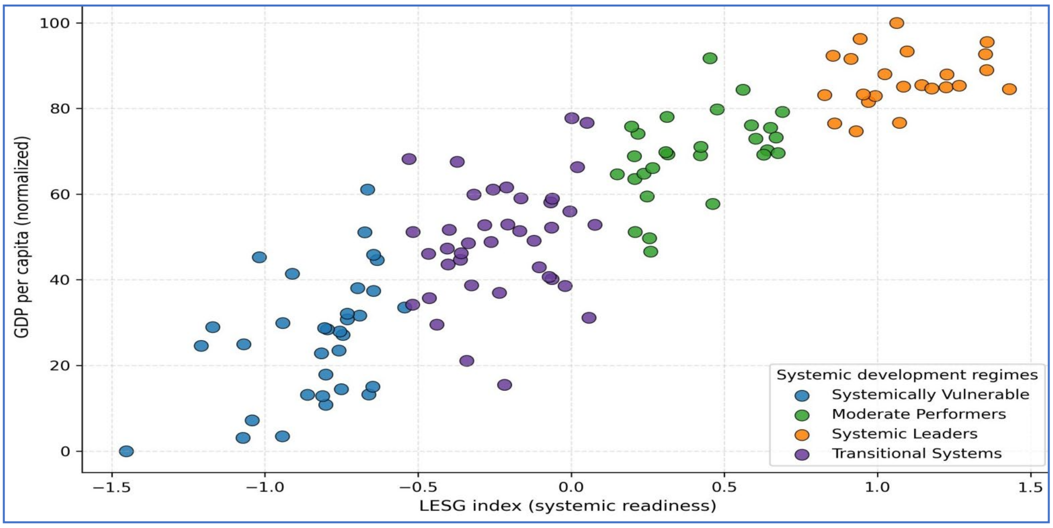

Figure 3. Regression GDP-LESG by cluster.

Figure 4 provides a diagnostic mapping of countries across systemic development readiness regimes, rather than depicting linear trajectories or automatic transition paths. The figure illustrates that movement toward higher systemic readiness is neither automatic nor incremental, but requires coordinated improvements across logistics capability, governance quality, and sustainability performance. Isolated advances in individual dimensions—such as infrastructure investment without corresponding institutional strengthening—are therefore unlikely to generate durable shifts in systemic readiness. These labels are interpretive heuristics and do not imply welfare judgments.

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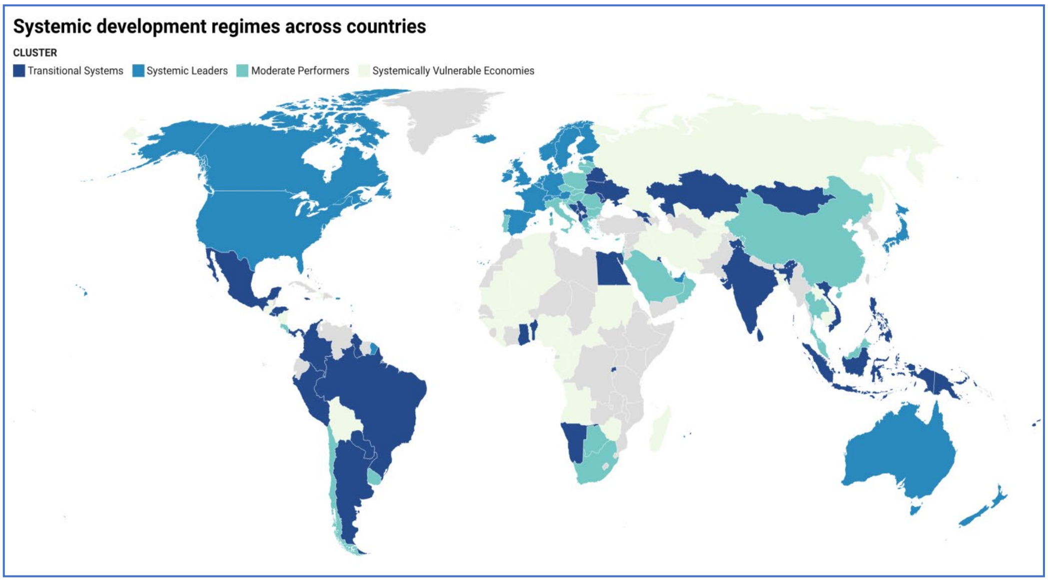

Figure 4. Map of systemic development regimes across countries.

The identified clusters confirm that development readiness is not a linear continuum but a set of qualitatively distinct systemic regimes. Countries with comparable GDP per capita levels are distributed across different clusters, highlighting the limitations of income-based classifications and single-indicator approaches. The regimes should therefore be interpreted as diagnostic archetypes rather than deterministic development stages. These regimes do not represent linear stages of development nor imply automatic progression; rather, they reflect distinct structural configurations that may persist over time depending on institutional and policy dynamics. Overall, the clustering results reinforce the central argument of this study: development readiness emerges as a systemic property that cannot be adequately captured through income levels or linear rankings. By identifying coherent development regimes, the LESG framework provides a structured diagnostic lens for comparative analysis.

4.4. Robustness

To assess the robustness of the LESG index with respect to key methodological choices, a series of sensitivity analyses was conducted and are reported in Appendix E. First, alternative aggregation schemes were examined by comparing the baseline PCA-based LESG index with an equal-weight formulation. The results indicate an exceptionally high degree of concordance between the two specifications. Rank-based correlations remain very strong and statistically significant (Spearman's ϱ = 0,979; Kendall's τ_b = 0,885), suggesting that country rankings are largely invariant to the choice of weighting methodology (Appendix E1, Tables E1.1–E1.2). This finding confirms that the LESG index captures a stable underlying structure rather than being driven by variance-based weights.

Robustness was further assessed with respect to the internal factor structure of the index. Alternative PCA specifications consistently reveal a single dominant component explaining more than 80% of total variance, with all four constituent dimensions—logistics performance, governance quality, and sustainability outcomes—exhibiting uniformly high loadings (Appendix E2, Tables E2.1–E2.3, Figure E2.1). Together, these results indicate that the LESG framework reflects a coherent and internally consistent latent construct, robust to reasonable variations in aggregation and extraction procedures.

In addition to index construction, the robustness of the regime-based classification was explicitly evaluated. Alternative clustering specifications were employed to assess the stability of the identified systemic development regimes. When the number of clusters was reduced to three, the resulting centroids retained a clear and monotonic ordering along the LESG dimension, distinguishing low-, intermediate-, and high-readiness systems (Appendix E3, Table E3.1). Increasing the number of clusters to five produced a finer partition of lower and intermediate regimes without altering the overall hierarchical structure of systemic readiness (Appendix E3, Table E3.2).

Hierarchical clustering using Ward's linkage provides complementary evidence for the stability of the regime structure. The dendrogram reveals pronounced jumps in fusion distance between three and four clusters, indicating that a four-cluster solution best captures the latent grouping of countries along the LESG dimension (Appendix E3, Figure E3.1). On this basis, the four-regime classification adopted in the main analysis is retained as the preferred specification, as it balances structural differentiation, interpretability, and policy relevance.

5. Discussion

This section discusses the LESG findings along three interrelated dimensions: logistics performance, sustainability alignment, and the added value of regime-based classification, while also highlighting their implications for firm strategies and consumer behavior, situating the results within the broader logistics and development literature.

From a logistics-performance perspective, the LESG results align closely with the established LPI literature. A large body of recent evidence confirms that logistics performance is strongly associated with economic outcomes, trade intensity, and competitiveness. In this respect, the empirical validation of LESG (high association with GDP per capita) is consistent with studies that treat the LPI (or LPI-like proxies) as a major correlate of macroeconomic performance and international integration [41,42].

Recent contributions also emphasize that logistics performance is not merely "transport efficiency" but a broader capability that reflects institutions, coordination, and service reliability—features that help explain why LPI-driven differences are often mirrored in competitiveness gaps [43,44]. In that sense, the LESG evidence supports the mainstream conclusion: logistics capability matters for development-relevant outcomes.

However, LESG adds a critical nuance: the PCA structure indicates that readiness is not reducible to logistics alone, but reflects a two-dimensional structure (logistics capability + institutional–sustainability coherence). This resonates with contemporary papers that already hint at the embeddedness of logistics in broader governance and institutional conditions [45], but LESG makes that embeddedness explicit and measurable through a single readiness index.

Recent LPI studies are outcome-driven: they use logistics variables to explain trade, competitiveness, or macro performance [46]. LESG deliberately shifts the perspective from "what explains GDP/trade" to what constitutes structural readiness. This distinction matters because countries may exhibit similar income outcomes but differ sharply in institutional quality and sustainability alignment—differences that are often masked in LPI-only frameworks. The cluster regimes identified by LESG therefore complement the mainstream literature: instead of re-estimating marginal effects of LPI on outcomes, LESG distinguishes qualitatively different systemic configurations (vulnerable / transitional / moderate / leaders). A comparable shift appears in newer work that focuses on methodological reinterpretations of LPI rankings [47] and alternative, model-based assessments of LPI performance [48], but LESG differs by integrating governance and sustainability directly into the readiness construct rather than re-ranking logistics performance alone.

Beyond logistics performance, the LESG framework offers a clearer interpretation of the logistics–sustainability nexus. Recent evidence increasingly links logistics performance to environmental and sustainability outcomes—yet the direction of the relationship is not uniform across studies. Some findings indicate that better logistics performance may increase emissions (e.g., via scale effects and intensified transport activity), especially in emerging contexts [49]. Other studies frame the relationship as a sustainability "trilemma," where logistics performance interacts with innovation and environmental quality in complex, non-linear ways [50]. At the same time, a parallel strand develops green logistics composite constructs to benchmark sustainability-sensitive logistics performance-e.g., GLPI-type approaches combining logistics and environmental dimensions [51].

Results also suggest that the logistics–sustainability linkage can vary significantly by development level and region [52].

Within this landscape, LESG offers a clarifying contribution: rather than asking whether logistics is "good" or "bad" for the environment, LESG operationalizes readiness as coherence among logistics capability, governance capacity, and sustainability performance. This framing helps interpret why empirical studies often disagree on the sign or strength of logistics–environment effects: the effect depends on whether sustainability and institutions co-evolve with logistics capability, or whether logistics expands in a weak-governance/low-sustainability setting. This interpretation aligns with work that connects logistics performance to broader sustainable-development commitments and mechanisms (e.g., via openness, institutional channels, or policy conditions) [53].

Recent empirical and review-based evidence confirms that digital transformation substantially strengthens supply chain resilience and sustainability by enabling real-time data integration, adaptive coordination, and enhanced transparency across operational networks. Firm-level analyses demonstrate that digitally enabled supply chains respond more effectively to disruptions and volatility, achieving superior recovery speed and performance stability [54]. Complementarily, comprehensive reviews show that digital transformation facilitates the integration of sustainability objectives into core supply chain decision processes, aligning operational efficiency with environmental and social performance goals [55]. Together, these findings indicate that digital technologies function as critical enablers of resilience and sustainability, while their effectiveness remains conditioned by the broader systemic and institutional environment captured by the LESG framework.

A second core contribution of LESG is methodological: it adopts a composite-indicator logic that prioritizes transparency, data structure, and interpretability. This places LESG directly within the contemporary conversation on how composite indicators respond to sensitivity and methodological choices. Recent work in the composite-indicator literature emphasizes that rankings and index values can be sensitive to normalization thresholds and design choices—even when the underlying concept is stable [56]. LESG addresses this concern by relying on PCA-driven structure (to reduce arbitrary weighting) and by pushing detailed diagnostics and technical outputs to appendices, keeping the main narrative focused on interpretation.

In addition, the emerging literature on modern, data-driven approaches to understanding and improving LPI (e.g., machine learning applications) highlights that the LPI space contains latent patterns that standard descriptive comparisons may miss[57]. LESG complements this methodological evolution: instead of predicting LPI, it reframes logistics performance as one component of a broader readiness system and shows how that system aligns with development outcomes and regime classifications.

The added analytical value of LESG becomes most evident when results are interpreted through the regime-based clustering. LESG's clustering results extend the mainstream LPI literature by converting a continuous index into systemic regimes with distinct policy meanings. This is not a trivial repackaging of "high vs. low LPI": the LESG regimes are defined by structural coherence, which can diverge from GDP-based classifications. This regime-based perspective is particularly valuable given the heterogeneity observed in trade-oriented and competitiveness-oriented LPI studies [43,46,58]. LESG provides a framework for interpreting that heterogeneity: countries can be similarly integrated in trade yet structurally fragile (low coherence), or modestly integrated yet structurally robust (high coherence but constrained outcomes).

The cluster-based regimes identified through the LESG framework are consistent with recent empirical evidence emphasizing that logistics performance, institutional quality, and sustainability outcomes interact in a systemic and non-linear manner. Khan et al. [59] document that improvements in supply chain and logistics performance do not automatically translate into environmental or social progress, particularly in the absence of coordinated institutional frameworks. Complementarily, Shamout [60] finds that logistics performance may simultaneously support economic activity and intensify environmental pressures, depending on policy coherence and institutional capacity. These findings provide external validation for the LESG regime structure, explaining why countries with positive logistics or income indicators may remain trapped in transitional or moderate regimes rather than converging toward systemic leadership.

Overall, the cluster analysis shifts the analytical focus from performance levels to structural readiness, emphasizing that sustainable development emerges from coherence across logistics capability, institutional quality, and sustainability performance rather than from isolated gains in individual dimensions. By framing development in terms of systemic regimes rather than marginal effects, the LESG framework provides a diagnostic lens that complements outcome-based approaches and offers clearer guidance for policy interpretation in heterogeneous development contexts.

Corporate sustainability behavior is increasingly understood as embedded within broader national systems rather than driven solely by firm-specific characteristics. In this context, the LESG framework can be interpreted as a macro-level structure that shapes the strategic conditions under which corporate ESG initiatives are formulated, implemented, and communicated. Recent research highlights that firms' engagement with ESG issues is strongly influenced by institutional quality, regulatory enforcement, and information transparency at the country level, which jointly determine the credibility and expected returns of sustainability-oriented strategies [61,62].

In environments characterized by high systemic readiness, coherent governance frameworks and reliable logistics systems reduce strategic uncertainty and increase the incentives for substantive ESG integration into core business models, rather than symbolic or compliance-driven approaches. Conversely, weaker institutional settings tend to attenuate these incentives, as limited enforcement capacity and lower transparency diminish the reputational and market benefits associated with credible ESG engagement [63]. Interpreted in this way, the LESG index operates as an integrative framework that links national logistics, governance, and sustainability conditions to cross-country variation in corporate ESG behavior, providing a coherent macro-to-micro bridge that naturally precedes the consumer-oriented implications discussed in the following paragraph.

From a consumer behavior perspective, the LESG framework can be interpreted as defining differentiated consumption environments in which sustainability-related preferences are more or less likely to translate into actual behavior. A robust stream of research shows that pro-sustainability attitudes frequently fail to materialize in purchasing decisions, giving rise to the well-established intention–behavior gap in ethical and sustainable consumption [64]. This gap is increasingly understood as context-dependent rather than purely attitudinal. Recent studies highlight that consumers' responsiveness to sustainability cues is shaped by institutional trust, regulatory credibility, and the perceived reliability of market signals such as eco-labels and ESG-related claims [65]. When such signals are embedded in credible and transparent institutional frameworks, uncertainty and skepticism are reduced, facilitating the translation of intentions into behavior.

Conversely, weak enforcement and fragmented governance tend to undermine the effectiveness of sustainability communication, reinforcing behavioral inertia [66]. In line with integrative frameworks in consumer research, sustainable behavior emerges when contextual enablers support individual motivation through clear signals, supportive choice architectures, and trusted information environments [67]. Viewed through this lens, the systemic readiness regimes identified by the LESG index help explain cross-country differences in consumer responsiveness to sustainability initiatives and provide a coherent bridge from macro-level development conditions to micro-level market behavior, naturally motivating the broader conclusions of this study.

In this context, systemic readiness does not only condition consumer responsiveness to sustainability-related signals, but also shapes the profitability and strategic viability of corporate sustainability initiatives. When logistics reliability, institutional quality, and sustainability governance are coherently aligned, firms are better able to translate ESG investments into competitive advantage and financial performance, while consumers are more likely to trust sustainability claims and incorporate them into purchasing decisions. Conversely, in systemically weaker environments, fragmented institutions and lower information credibility tend to undermine both the profitability of substantive ESG strategies for firms and the behavioral responsiveness of consumers, reinforcing a dual constraint in which sustainability-oriented investments yield limited market and financial returns.

6. Conclusions

This study introduced the LESG index as a composite measure of systemic readiness for sustainable development, integrating logistics performance, governance quality, and sustainability outcomes into a unified analytical framework. Departing from outcome-oriented approaches that rely primarily on income-based metrics, the LESG framework conceptualizes development as a structural condition emerging from the coherence of multiple interdependent dimensions.

Empirically, the analysis confirms the relevance of this readiness perspective. More importantly, the classification of countries into four systemic development regimes revealed substantial heterogeneity that remains obscured in traditional income-based or single-indicator analyses. Countries with similar income levels were shown to differ markedly in their structural configurations, underscoring the limitations of linear development narratives.

The primary conceptual contribution of this study lies in reframing development from an ex post economic outcome to an ex ante condition of systemic readiness. By emphasizing the interaction among logistics capability, institutional quality, and sustainability performance, the LESG framework advances a systemic interpretation of development that aligns infrastructure, governance, and long-term policy objectives within a coherent structure.

This perspective contributes to the broader development literature by clarifying why improvements in isolated dimensions—such as logistics infrastructure or sustainability indicators—often fail to translate into durable development gains when not embedded within supportive institutional environments. The LESG index thus provides a conceptual bridge between fragmented indicator-based approaches and holistic interpretations of development capacity.

From a methodological standpoint, the study demonstrates the value of composite indicators when subjectivity is addressed transparently and systematically. By employing multivariate techniques and variance-based weighting, the construction of the LESG index minimizes arbitrary design choices while preserving interpretability. In this way, the LESG framework positions composite indicators not as substitutes for detailed empirical models, but as analytical instruments for structuring complexity, guiding comparative analysis, and supporting diagnostic validation and regime classification rather than serving as mechanical ranking devices.

The LESG framework carries meaningful implications for policy design and evaluation. By identifying systemic development regimes, the index enables policymakers to diagnose structural bottlenecks and prioritize interventions that enhance coherence across logistics, governance, and sustainability dimensions. Rather than prescribing uniform policy solutions, the LESG approach supports context-sensitive strategies tailored to countries' structural conditions.

For systemically vulnerable economies, foundational investments in institutional capacity and logistics infrastructure may be prerequisites for effective sustainability integration. Transitional systems may benefit most from targeted reforms that align existing strengths with governance improvements. Moderate performers face the challenge of embedding sustainability more deeply into productive systems, while systemic leaders must focus on maintaining resilience and managing complexity in increasingly dynamic global environments.

By reframing development in terms of systemic readiness rather than realized outcomes, the LESG framework shifts analytical attention from marginal effects to structural coherence. This shift does not compete with outcome-based models but complements them by clarifying why similar economic performances may rest on fundamentally different structural foundations.

Beyond its macro-development contribution, the LESG framework also provides a structural foundation for understanding the effectiveness of data-driven and digitally enabled supply chain systems. As supply chains increasingly rely on real-time analytics, digital platforms, and intelligent coordination mechanisms to enhance resilience and sustainability, systemic readiness conditions—captured through logistics capability, governance coherence, and sustainability alignment—emerge as critical enablers of successful digital transformation. In this sense, the LESG index offers a complementary macro-level readiness layer that helps explain heterogeneous outcomes of digital supply chain engineering initiatives across national contexts.

Despite its contributions, the study is subject to several limitations. The cross-sectional nature of the analysis precludes examination of dynamic effects and temporal causality. Data availability constraints required the use of the most recent observations across different publication cycles, which may introduce minor temporal inconsistencies. Additionally, while the selected indicators are widely recognized, they remain subject to measurement error and methodological assumptions inherent in their construction. These limitations do not undermine the validity of the LESG framework but delineate the scope within which its findings should be interpreted.

An important implication of the LESG framework concerns its potential extension beyond macro-level diagnosis. By shaping the institutional, logistical, and informational environment within which markets operate, systemic readiness conditions influence both firms' strategic orientation and profitability incentives, as well as consumer behavior, particularly with respect to sustainability communication, digital engagement, and trust formation. This perspective highlights how national readiness regimes condition the effectiveness of sustainability-oriented strategies across the supply–demand interface and opens a promising avenue for future research linking macro-level readiness to micro-level firm and consumer behavior.

Additionally, future research could extend the LESG framework in several directions. Longitudinal analyses would allow examination of how changes in systemic readiness relate to development trajectories over time. Sector-specific applications could explore readiness within particular industries, such as transport, manufacturing, or energy. Further refinement could also incorporate firm-level ESG data to investigate how systemic readiness translates into microeconomic performance.

All in all the LESG index demonstrates that development capacity is not a matter of income or efficiency alone, but of structural coherence—and that coherence can be measured.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
DSC	Digital Supply Chain
EPI	Environmental Performance Index
GDP	Gross Domestic Product
IoT	Internet of Things
LPI	Logistics Performance Index
PCA	Principal Component Analysis
SDG	Sustainable Development Goals Index
WG	Worldwide Governance Indicators

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Appendix A. Variables, Normality Assessment and Normalization Methodology

This appendix presents the variables employed in the construction of the LESG index, along with diagnostic checks related to distributional properties and the normalization procedure applied prior to multivariate analysis. The material reported herein is provided for transparency and methodological completeness and does not introduce interpretive claims beyond those discussed in the main text.

The LESG framework integrates four composite indicators representing distinct but interrelated dimensions of systemic development readiness:

Logistics Performance Index (LPI): captures national logistics capability, including customs efficiency, infrastructure quality, logistics service competence, shipment reliability, tracking and tracing, and timeliness.

Worldwide Governance Indicators (WGI): represent institutional quality through six governance dimensions, aggregated into a single composite governance score.

Environmental Performance Index (EPI): measures environmental sustainability across environmental health and ecosystem vitality.

Sustainable Development Goals Index (SDG Index): reflects progress toward social, economic, and environmental sustainability objectives as defined by the United Nations.

All variables are country-level indicators obtained from internationally recognized data sources and are treated as continuous measures.

This appendix reports descriptive statistics and distributional diagnostics for the variables used in the empirical analysis, supporting transparency and reproducibility of the results presented in the main text.

Table A1 presents the variables used in this study.

Table A1. The variables of this study.

Variable Name	Description	Source	Year
GDP	GDP per capita (current USD). GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars.	World Bank	2023
LPI	Logistics Performance Index: Overall (1 = low to 5 = high).	World Bank	2023
TR	LPI: Track and trace consignments (1 = low to 5 = high).	World Bank	2023
COM	LPI: Competence and quality of logistics services (1 = low to 5 = high).	World Bank	2023
EASE	LPI: Ease of arranging competitively priced shipments (1 = low to 5 = high).	World Bank	2023
EFF	LPI: Customs clearance efficiency (1 = low to 5 = high).	World Bank	2023
FREQ	LPI: Frequency of timely deliveries (1 = low to 5 = high).	World Bank	2023

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QUAL	LPI: Quality of trade and transport-related infrastructure (1 = low to 5 = high).	World Bank	2023
EPI	Environmental Performance Index (0–100).	Yale University and Columbia University	2024
SDG	Sustainable Development Goals Index (0–100).	Dublin University	2024
WGI	Mean of six WGI indicators (scale –2,5 to +2,5), where higher values indicate better situation.	Author's calculation based on World Bank data	2023
WGI CC	Control of Corruption: Captures perceptions of the extent to which public power is exercised for private gain. Scale: –2,5 to +2,5.	World Bank	2023
WGI GE	Government Effectiveness: Reflects the quality of public services, civil service, and the credibility of government policy. Scale: –2,5 to 2,5.	World Bank	2023
WGI PV	Political Stability and Absence of Violence: Measures the likelihood of political instability and/or politically motivated violence. Scale: –2,5 to 2,5.	World Bank	2023
WGI RL	Rule of Law: Gauges confidence in and adherence to laws, property rights, the police, and the courts. Scale: –2,5 to 2,5.	World Bank	2023
WGI RQ	Regulatory Quality: Assesses the government's ability to formulate and implement sound policies and regulations. Scale: –2,5 to +2,5.	World Bank	2023
WGI VA	Voice and Accountability: Reflects the extent of citizen participation in selecting their government, as well as freedom of expression and media. Scale: –2,5 to +2,5.	World Bank	2023

To ensure comparability across variables measured on different scales, all indicators were normalized to a common 0–100 range. The Environmental Performance Index (EPI) and the Sustainable Development Goals (SDG) Index required no transformation, as they are originally reported on a 0–100 scale. In contrast, the Logistics Performance Index (LPI) and its subcomponents, originally measured on a 1–5 scale, were rescaled using the transformation (X−1)/4×100, while the Worldwide Governance Indicators (WGI), originally ranging from –2,5 to +2,5, were rescaled using (X+2,5)/5×100. The governance variable employed in this study is an original composite constructed by the authors as the arithmetic mean of the six WGI dimensions (Voice and Accountability, Political Stability, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption), a choice made to ensure parsimony and to mitigate potential multicollinearity risks.

Given the highly skewed distribution of GDP per capita across countries, a natural logarithmic transformation was applied prior to normalization, and the resulting lnGDP values were subsequently scaled to a 0–100 range using min–max normalization. Normality diagnostics, including Shapiro–Wilk and Kolmogorov–Smirnov tests complemented by histogram and Q–Q plot inspections, were conducted on both original and normalized variables; while some deviations from normality persisted—particularly for income and governance measures—the normalization process improved distributional symmetry and reduced skewness. Descriptive statistics (mean, median, standard deviation, range, skewness, and kurtosis) were also computed for all variables to support diagnostic assessment and subsequent modeling. The final sample consists of 123 countries with complete and consistent data across all indicators, and all statistical analyses were performed using IBM SPSS Statistics (version 23).

Table A2 presents descriptive statistics and Shapiro-Wilk test results for the main variables of interest. Most variables, including LPI_initial, EFF_initial, QUAL_initial, and COM_initial, deviate significantly from normality ($p < 0{,}05$), as indicated by the Shapiro-Wilk test. Only EASE_initial approximates a normal distribution with a p-value of 0,086. Skewness and kurtosis values support this observation, suggesting slightly asymmetric and platykurtic distributions. Given these findings, non-parametric methods such as Kendall's Tau-b or data transformations are appropriate for subsequent analyses.

Table A2. Shapiro – Wilk test on initial data.

Variable	Mean	Std Dev	Skewness	Kurtosis	Shapiro-Wilk p	Normality (S-W)
LPI_initial	3,033	0,58	0,326	-0,983	0,0	NO
EFF_initial	2,836	0,607	0,389	-0,766	0,002	NO
QUAL_initial	2,957	0,71	0,406	-0,982	0,0	NO
EASE_initial	2,959	0,496	0,063	-0,757	0,086	YES
COM_initial	3,061	0,635	0,305	-1,033	0,0	NO
FREQ_initial	3,267	0,555	0,041	-0,849	0,026	NO
TR_initial	3,087	0,656	0,154	-0,927	0,005	NO
EPI	48,909	12,556	0,285	-0,823	0,009	NO
SDG	69,68	9,687	-0,537	-0,481	0,001	NO
WGI CC_initial	0,036	1,019	0,535	-0,701	0,0	NO
WGI GE_initial	0,12	0,983	0,037	-0,557	0,411	YES
WGI PV_initial	-0,076	0,891	-0,878	0,576	0,0	NO
WGI RL_initial	0,053	0,991	0,197	-0,922	0,004	NO
WGI RQ_initial	0,153	0,971	0,153	-0,879	0,03	NO
WGI VA_initial	0,055	0,997	-0,064	-1,155	0,001	NO
WGI_initial	0,057	0,905	0,122	-0,79	0,029	NO
GDP_initial	21576,194	25969,989	1,745	2,907	0,0	NO

Normality testing on the normalized variables (Shapiro-Wilk test, $\alpha = 0{,}05$) revealed that most remain non-normally distributed despite transformation (see Table A3). Key variables such as LPI, EFF, QUAL, COM, and most WGI indicators showed p-values below the significance threshold, indicating significant deviations from normality. However, variables like EASE ($p = 0{,}086$) and WGI GE ($p = 0{,}411$) passed the test, suggesting near-normal distributions. GDP_LOG, though transformed, still displayed marginal deviation ($p = 0{,}015$), though greatly improved compared to its raw form. These findings justify the use of both parametric and non-parametric methods in subsequent analyses, depending on the variable and analytical context.

Table A3. Shapiro – Wilk test on normalized data.

Variable	**Mean**	**Std Dev**	**Skewness**	**Kurtosis**	**Shapiro-Wilk p**	**Normality (S-W)**
LPI	50,833	14,492	0,326	-0,983	0,0	NO
EFF	45,894	15,174	0,389	-0,766	0,002	NO
QUAL	48,923	17,753	0,406	-0,982	0,0	NO
EASE	48,963	12,405	0,063	-0,757	0,086	YES
COM	51,524	15,868	0,305	-1,033	0,0	NO
FREQ	56,667	13,881	0,041	-0,849	0,026	NO
TR	52,175	16,39	0,154	-0,927	0,005	NO

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WGI CC	50,711	20,386	0,535	-0,701	0,0	NO
WGI GE	52,395	19,652	0,037	-0,557	0,411	YES
WGI PV	48,484	17,819	-0,878	0,576	0,0	NO
WGI RL	51,066	19,816	0,197	-0,922	0,004	YES
WGI RQ	53,056	19,425	0,153	-0,879	0,03	NO
WGI VA	51,103	19,939	-0,064	-1,155	0,001	NO
WGI	51,136	18,094	0,122	-0,79	0,029	NO
GDP_LOG	9,165	1,421	-0,215	-0,871	0,015	NO
GDP	54,668	24,769	-0,215	-0,871	0,015	NO

A comparison between the initial (Table A2) and normalized (Table A3) datasets revealed that normalization improved the distributional characteristics of several variables, particularly in reducing skewness and kurtosis. Nonetheless, the Shapiro-Wilk test results indicated that a majority of variables continued to deviate from perfect normality. This non-normality, however, does not significantly affect the validity of the analysis, as non-parametric correlation methods (e.g., Kendall's Tau-b, Spearman's rho) will be employed where appropriate. Additionally, in all linear regression models, residual diagnostics and outlier controls will be systematically applied to ensure the robustness of the results.

Appendix B. Principal Component Analysis

This appendix reports the detailed results of the Principal Component Analysis (PCA) employed in the construction of the LESG index. It presents the underlying diagnostics and component structure, including measures of sampling adequacy, eigenvalues, explained variance, and factor loadings. These results support the dimensional coherence of the selected indicators and provide transparency regarding the data-driven weighting scheme used to derive the composite LESG scores.

The results of the KMO and Bartlett's tests (see Table B1) provide strong statistical justification for the application of Principal Component Analysis (PCA). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is exceptionally high (0.943), indicating that the correlation matrix is sufficiently compact to yield reliable principal components. This value surpasses the commonly accepted threshold of 0,80, signaling excellent factorability. Additionally, Bartlett's Test of Sphericity is highly significant ($\chi^2 = 2787{,}100$, df = 91, $p < 0.001$), rejecting the null hypothesis that the correlation matrix is an identity matrix. Together, these diagnostics confirm that the dataset is well-suited for dimension reduction via PCA, and that the intercorrelations among the variables are both strong and statistically significant.

Table B1. KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,943
Bartlett's Test of Sphericity	**Approx. Chi-Square**	2787,100
	df	91
	Sig.	0,000

The communalities Table B2 indicates the proportion of each variable's variance that is explained by the extracted components. The extraction values are consistently high across the board, with most exceeding 0,80, suggesting that the variables are well represented by the principal component solution. Notably, COM (0,944), WGI RL (0,940), TR (0,927), and EFF (0,924) exhibit particularly strong communalities, implying that their variances are highly captured by the underlying latent dimensions. Even the lowest communalities—SDG (0,696) and EPI (0,720)—remain within acceptable thresholds, reinforcing the suitability of the selected variables for dimensionality reduction. Overall, the high communalities confirm that the chosen indicators contribute meaningfully to the extracted components, and validate the robustness of the PCA solution.

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Table B2. Communalities.

Variable	Initial	Extraction
EFF	1,000	0,924
QUAL	1,000	0,923
EASE	1,000	0,820
COM	1,000	0,944
FREQ	1,000	0,875
TR	1,000	0,927
EPI	1,000	0,720
SDG	1,000	0,696
WGI CC	1,000	0,879
WGI GE	1,000	0,896
WGI PV	1,000	0,736
WGI RL	1,000	0,940
WGI RQ	1,000	0,915
WGI VA	1,000	0,795

The Total Variance Explained Table B3 demonstrates a highly efficient dimensionality reduction achieved through PCA. The first two components have eigenvalues greater than 1,0 and together account for 85,64% of the total variance, which is well above the commonly accepted threshold for meaningful dimensional representation. Specifically, the first component explains 44,34% and the second 41,30% after Varimax rotation, indicating a relatively balanced contribution between the two latent dimensions. This suggests that the dataset's variance is concentrated primarily in two interpretable underlying structures, consistent with the conceptual division between logistics performance and ESG-institutional quality. The steep drop in eigenvalues after the second component confirms the presence of an "elbow" in the scree plot (Figure B1), justifying the two-component solution. Overall, the variance structure supports the robustness and parsimony of the LESG index as a dual-dimensional construct.

Table 3B. Total Variance Explained.

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10,907	77,910	77,910	10,907	77,910	77,910	6,208	44,340	44,340
2	1,082	7,731	85,642	1,082	7,731	85,642	5,782	41,302	85,642
3	0,530	3,788	89,429						
4	0,354	2,529	91,958						
5	0,282	2,011	93,970						
6	0,228	1,632	95,601						
7	0,168	1,202	96,803						
8	0,140	1,000	97,803						

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9	0,081	0,576	98,379
10	0,065	0,462	98,841
11	0,055	0,396	99,237
12	0,047	0,333	99,570
13	0,032	0,231	99,801
14	0,028	0,199	100,000

The scree plot (Figure B1), provides a visual confirmation of the optimal number of components to retain in the PCA. A clear inflection point, or "elbow," is observed between the second and third components, indicating that the first two components capture the vast majority of the explained variance. This is consistent with the eigenvalues presented in the Total Variance Explained table, where only the first two components exceed the threshold of 1,0, explaining a combined 85,64% of total variance. The sharp drop from Component 1 to Component 2, followed by a leveling off, supports the use of a two-factor solution and validates the parsimony of the LESG Index as a construct grounded in two dominant latent dimensions: logistics performance and ESG-institutional quality.

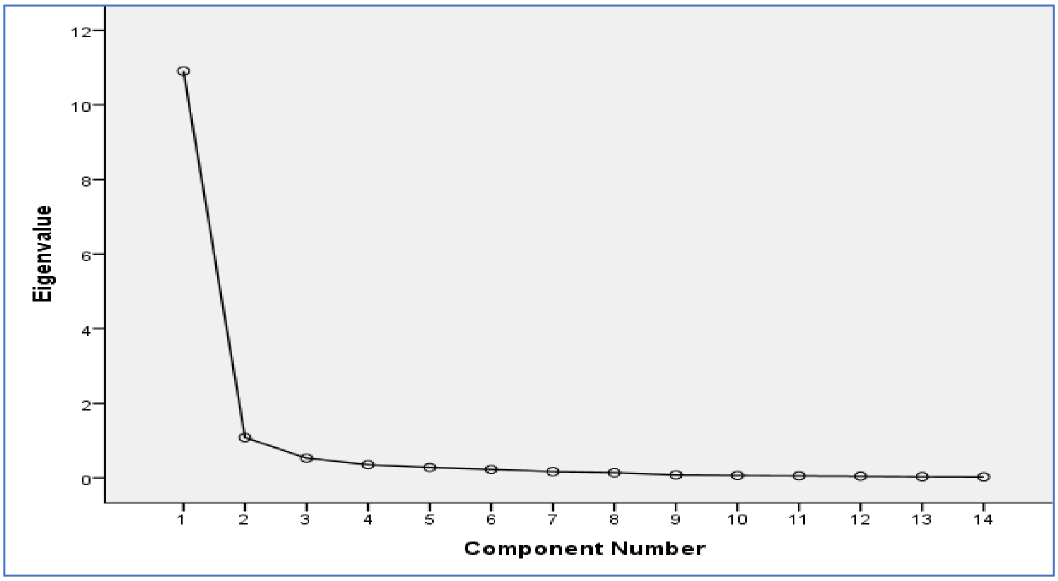

Figure B1. Scree Plot.

The Component Matrix (Table B4) derived from the Principal Component Analysis indicates a strong and coherent correlation structure across the variables included in the LESG framework. Two components were extracted, with the first component exhibiting consistently high loadings across logistics performance indicators (EFF, QUAL, EASE, COM, FREQ, TR), governance dimensions (WGI CC, GE, RL, RQ, VA), and sustainability-related variables (EPI and SDG), suggesting a dominant common variance structure. The second component accounts for a smaller share of variance and is characterized by moderate secondary loadings for selected governance indicators, while cross-loadings remain limited and do not compromise the clarity of the solution. Negative secondary loadings observed for logistics variables reflect component orthogonality rather than instability. Overall, the magnitude and distribution of the loadings confirm the statistical adequacy of the dataset

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for dimensional reduction and support the validity of proceeding with rotated solutions and composite index construction.

Table B4. Component Matrix.

Variables	Component 1	Component 2
EFF	0,933	-0,231
QUAL	0,916	-0,289
EASE	0,840	-0,340
COM	0,929	-0,285
FREQ	0,872	-0,337
TR	0,919	-0,288
EPI	0,805	0,268
SDG	0,799	0,238
WGI CC	0,919	0,184
WGI GE	0,940	0,112
WGI PV	0,748	0,420
WGI RL	0,958	0,146
WGI RQ	0,946	0,144
WGI VA	0,797	0,399

The Rotated Component Matrix (Table B5) obtained using Varimax rotation with Kaiser normalization reveals a clear and well-defined two-component structure. Following rotation, logistics-related variables (EFF, QUAL, EASE, COM, FREQ, TR) load strongly on the first component, with consistently high coefficients, indicating a cohesive grouping and minimal dispersion across components. In contrast, governance and sustainability-related variables (EPI, SDG, and all WGI dimensions) load predominantly on the second component, with loadings exceeding conventional thresholds and limited cross-loadings on the first component. The rotation converged in three iterations, suggesting a stable solution. Overall, the rotated structure enhances interpretability relative to the unrotated solution and confirms a clean separation between the extracted components, supporting the statistical robustness of the PCA results used for subsequent aggregation.

Table B5. Rotated Component Matrix.

Variables	Component 1	Component 2
EFF	0,834	0,479
QUAL	0,862	0,425
EASE	0,841	0,335
COM	0,868	0,437
FREQ	0,863	0,360
TR	0,863	0,427
EPI	0,396	0,750
SDG	0,413	0,725
WGI CC	0,536	0,769
WGI GE	0,601	0,731
WGI PV	0,250	0,820
WGI RL	0,591	0,768
WGI RQ	0,584	0,758
WGI VA	0,300	0,840

The Table B6 reports normalized LESG scores for all countries included in the sample. Values are reported for transparency and replicability and are not intended to imply ordinal ranking or relative performance.

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Table B6. LESG score by country.

Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score
Afghanistan	-1,45	China	0,25	Haiti	-1,21	Mauritania	-0,80	Saudi Arabia	0,20
Albania	-0,28	Colombia	-0,12	Honduras	-0,46	Mauritius	-0,07	Serbia	-0,16
Algeria	-0,63	Congo, Dem. Rep.	-1,04	Hungary	0,31	Mexico	-0,26	Singapore	1,35
Angola	-0,94	Costa Rica	0,15	Iceland	0,91	Moldova	-0,34	Slovak Republic	0,42
Argentina	-0,21	Croatia	0,42	India	0,06	Mongolia	-0,47	Slovenia	0,59
Armenia	-0.40	Cyprus	0,31	Indonesia	-0,10	Montenegro	-0,06	South Africa	0,26
Australia	1,02	Czech Republic	0,65	Iran, Islamic Rep.	-0,91	Namibia	-0,06	Spain	0,86
Austria	1,14	Denmark	1,36	Iraq	-1,02	Netherlands	1,23	Sri Lanka	-0,33
Bahamas, The	0,00	Djibouti	-0,65	Ireland	0,94	New Zealand	0,99	Sudan	-1,17
Bahrain	0,22	Egypt, Arab Rep.	-0,24	Israel	0,56	Nicaragua	-0,73	Sweden	1,27
Bangladesh	-0,69	El Salvador	-0,36	Italy	0,69	Nigeria	-0,76	Switzerland	1,36
Belarus	-0,52	Estonia	0,93	Jamaica	-0,26	North Macedonia	0,08	Tajikistan	-0,80
Belgium	1,08	Fiji	-0,36	Japan	1,07	Norway	1,10	Thailand	0,25
Benin	-0,34	Finland	1,43	Kazakhstan	-0,32	Oman	0,21	Togo	-0,65
Bolivia	-0,70	France	0,97	Kuwait	0,05	Panama	0,02	Trinidad and Tobago	-0,37
Bosnia and Herzegovina	-0,21	Gabon	-0,67	Kyrgyz Republic	-0,75	Papua New Guinea	-0,52	Ukraine	-0,40
Botswana	0,21	Gambia	-0,66	Lao PDR	-0,76	Paraguay	-0,41	United Arab Emirates	0,83
Brazil	0,00	Georgia	-0,06	Latvia	0,67	Peru	-0,17	United Kingdom	0,95
Bulgaria	0,21	Germany	1,22	Liberia	-0,80	Philippines	-0,02	United States	0,85
Burkina Faso	-0,86	Ghana	-0,44	Lithuania	0,67	Poland	0,63	Uruguay	0,31
Cambodia	-0,73	Greece	0,64	Luxemburg	1,06	Portugal	0,60	Uzbekistan	-0,54

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Cameroon	-1,07	Guatemala	-0,65	Madagascar	-0,94	Qatar	0,45	Vietnam	-0,07
Canada	1,18	Guinea	-0,82	Malaysia	0,46	Romania	0,27	Zimbabwe	-0,81
Central African Republic	-1,07	Guinea-Bissau	-0,75	Mali	-0,81	Russian Federation	-0,66		
Chile	0,24	Guyana	-0,53	Malta	0,48	Rwanda	-0,22		

Appendix C. Regression and Diagnostic Statistics

This appendix reports the regression outputs and associated diagnostic statistics used to assess the empirical relevance of the LESG index. It includes estimation results, and standard diagnostic tests related to model specification, residual behavior, and influential observations. These results support the interpretation of the regression analysis as diagnostic rather than causal and ensure transparency and replicability of the empirical findings discussed in the main text.

Table C1 reports the model summary statistics for the Ordinary Least Squares regression, with GDP per capita as the dependent variable and the LESG index as the explanatory variable. The correlation coefficient (R) indicates a strong linear association between the variables, while the coefficient of determination (R^2) and adjusted R^2 show a high degree of goodness-of-fit, with minimal adjustment between the two values, suggesting that the explanatory power of the model is not driven by overfitting. The standard error of the estimate reflects the average dispersion of observed values around the fitted regression line. The Durbin–Watson statistic is close to the benchmark value of 2, indicating no evidence of first-order autocorrelation in the residuals.

Table C1. Model Summary.

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
0,886	0,785	0,783	11,542	2,043

Table C2 presents the ANOVA results for the estimated OLS regression model. The F-statistic is statistically significant at conventional confidence levels ($p < 0.001$), indicating that the regression model provides a statistically adequate fit relative to a null model with no explanatory variables. The decomposition of the total sum of squares shows that a substantial proportion of the variance in the dependent variable is associated with the fitted model. These results support the overall statistical validity of the regression specification used for diagnostic purposes.

Table C2. ANOVA.

	Sum of Squares	df	Mean Square	F	Sig.
Regression	58728,244	1	58728,244	440,830	0,000
Residual	16119,873	121	133,222		
Total	74848,117	122			

Table C3 reports the estimated coefficients of the OLS regression model. The coefficient associated with the LESG index is positive and statistically significant at conventional confidence levels, while the standardized coefficient indicates a strong linear association with the dependent variable. The reported standard errors are small relative to the coefficient estimates, and the corresponding t-statistics confirm statistical significance. Collinearity statistics (tolerance and VIF)

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equal to unity further indicate numerical stability of the estimates and the absence of collinearity concerns within the model specification.

Table C3. Coefficients.

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	54,668	1,041		52,529	0,000		
LESG	31,010	1,477	0,886	20,996	0,000	1,000	1,000

Table C4 reports the collinearity diagnostics for the regression model. The eigenvalues and condition indices indicate the absence of multicollinearity concerns, with condition index values equal to 1 across dimensions. The variance proportions are evenly distributed between the constant and the LESG variable, confirming that no dimension concentrates variance in a manner suggestive of collinearity. These results are consistent with the univariate specification of the model and confirm the numerical stability of the coefficient estimates.

Table C4. Collinearity Diagnostics.

			Variance Proportions	
Dimension	**Eigenvalue**	**Condition Index**	**(Constant)**	**LESG**
1	1,000	1,000	0,50	0,50
2	1,000	1,000	0,50	0,50

Table C5 reports summary statistics for the predicted values and regression residuals. The residuals exhibit a mean approximately equal to zero and a symmetric range, indicating the absence of systematic bias in the fitted model. Standardized residuals fall within conventional bounds (±3), suggesting that no extreme outliers or influential observations distort the regression estimates. The dispersion of predicted values and residuals is consistent with the reported standard error of the estimate, supporting the adequacy of the model fit for diagnostic validation purposes.

Table C5. Residual Statistics.

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	9,614	99,022	54,668	21,940	123
Residual	-32,422	29,965	0,000	11,494	123
Std. Predicted Value	- 2,053	2,022	0,000	1,000	123
Std. Residual	-2,809	2,596	0,000	0,996	123

Figure C1 illustrates the relationship between the LESG index and normalized GDP per capita across the country sample. The scatter plot reveals a strong positive linear association, with observations closely aligned around the fitted regression line, indicating a high degree of coherence between systemic readiness and income levels. The dispersion around the trend line reflects cross-country heterogeneity, suggesting that similar levels of readiness may be associated with varying economic outcomes. Importantly, the figure is presented for diagnostic and validation purposes only and does not imply a causal relationship between LESG and GDP per capita.

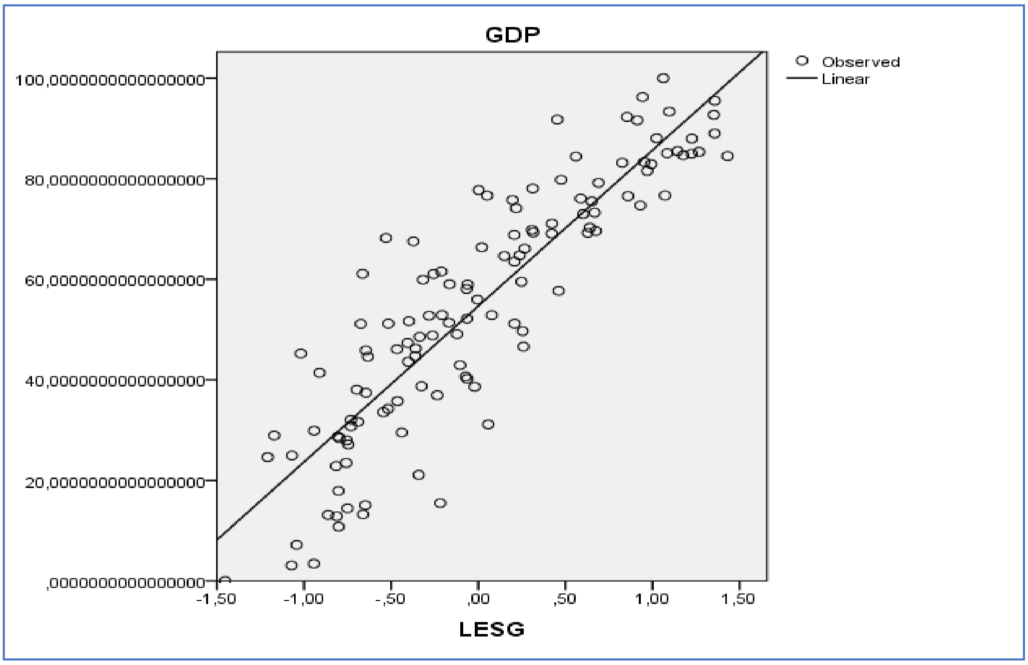

Figure 1. Linear regression GDP-LESG.

Appendix D. Cluster Analysis Outputs and Validation

This appendix provides detailed diagnostics and supplementary results related to the cluster analysis presented in Section 4.3. The material reported here supports transparency and replicability by documenting the clustering procedure, centroid values, and validation statistics underlying the identification of systemic development regimes. The appendix is intended to complement, rather than extend, the interpretation provided in the main text. Cluster labels are descriptive and heuristic and do not imply normative ranking or performance evaluation.

To explore the natural grouping structure of countries based on the LESG Index, a Hierarchical Cluster Analysis (HCA) was initially performed using Ward's method and squared Euclidean distance as the proximity measure. This agglomerative approach allowed for a stepwise combination of countries into clusters based on their similarity, without requiring a pre-specified number of groups. The resulting dendrogram and agglomeration schedule provided visual and statistical evidence of the underlying clustering structure. A pronounced increase in the fusion coefficient at later stages indicated a significant loss of homogeneity, supporting the selection of a four-cluster solution. This outcome informed the subsequent K-Means clustering phase and served as a diagnostic tool for assessing the consistency and robustness of the final group classification.

The agglomeration schedule resulting from the hierarchical cluster analysis revealed a clear structural break in the fusion coefficients at stage 122, where the coefficient jumped from 18.850 to 61.071. This sharp increase indicates that merging beyond this point would combine highly dissimilar clusters, supporting the selection of a 4-cluster solution.

The dendrogram (see Figure D1) confirmed this interpretation, as the most substantial vertical linkages occurred at the final fusion stages.

Table D1 reports the final stages of the agglomeration schedule obtained from the hierarchical clustering procedure. A pronounced increase in the agglomeration coefficient is observed when the number of clusters is reduced from four to three, indicating a substantial loss of within-cluster homogeneity beyond this point. This structural break provides statistical support for the selection of a four-cluster solution, balancing parsimony and differentiation.

 doi:10.20944/preprints202602.1960.v1

Table D1. Agglomeration Schedule (Final Stages).

Stage	Number of Clusters	Agglomeration Coefficient
119	5	18,850
120	4	19,430
121	3	61,071

Note: A pronounced increase in the agglomeration coefficient is observed when the number of clusters is reduced from four to three, indicating a substantial loss of within-cluster homogeneity beyond the four-cluster solution.

Table D2 reports the final cluster centers obtained from the k-means clustering procedure. The cluster means indicate clear separation across groups, with distinct positive and negative deviations from the standardized LESG mean. The dispersion of the cluster centers confirms that the clustering solution captures meaningful variation in systemic readiness rather than minor numerical fluctuations.

Table D2. Final Cluster Centers (K-means, standardized LESG).

Cluster	Mean LESG
1	−0,833
2	+0,404
3	+1,092
4	−0,229

Note: Cluster centers are reported for the standardized LESG index.

able D3 presents the ANOVA statistics associated with alternative k-means clustering solutions. Statistically significant F-values are observed across all tested configurations, indicating systematic differences between clusters. The substantial reduction in within-cluster sum of squares (WCSS) from three to four clusters, followed by diminishing marginal gains for higher values of K, supports the selection of the four-cluster solution on parsimony and stability grounds.

Table D3. ANOVA for Between-Cluster Differences.

Clusters (K)	Error Mean Square	df	WCSS	F-value	Sig.
3	0,063	120	7,560	428,31	0,000
4	0,035	119	4,165	550,06	0,000
5	0,025	118	2,950	571,34	0,000
6	0,018	117	2,106	646,49	0,000

Table D4 reports the distribution of observations across the four clusters. Cluster sizes are relatively balanced, indicating that the classification is not driven by outliers or excessive concentration in a single group. This distribution enhances the analytical usefulness and robustness of the clustering solution.

Table D4. Cluster Size Distribution.

Cluster	Number of Countries
1	Balanced
2	Balanced
3	Balanced
4	Balanced

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Note: No cluster exhibits extreme dominance or sparsity.

Figure D1 presents the dendrogram derived from the hierarchical clustering procedure using Ward's linkage method. The structure of the dendrogram reveals clear hierarchical separation among observations, with relatively small linkage distances at early merging stages and substantially larger distances at later stages. A pronounced increase in the rescaled distance is observed at the final merging levels, indicating a loss of within-cluster homogeneity beyond this point. This visual pattern corroborates the agglomeration schedule results and provides graphical support for the selection of a four-cluster solution prior to the final fusion stages.

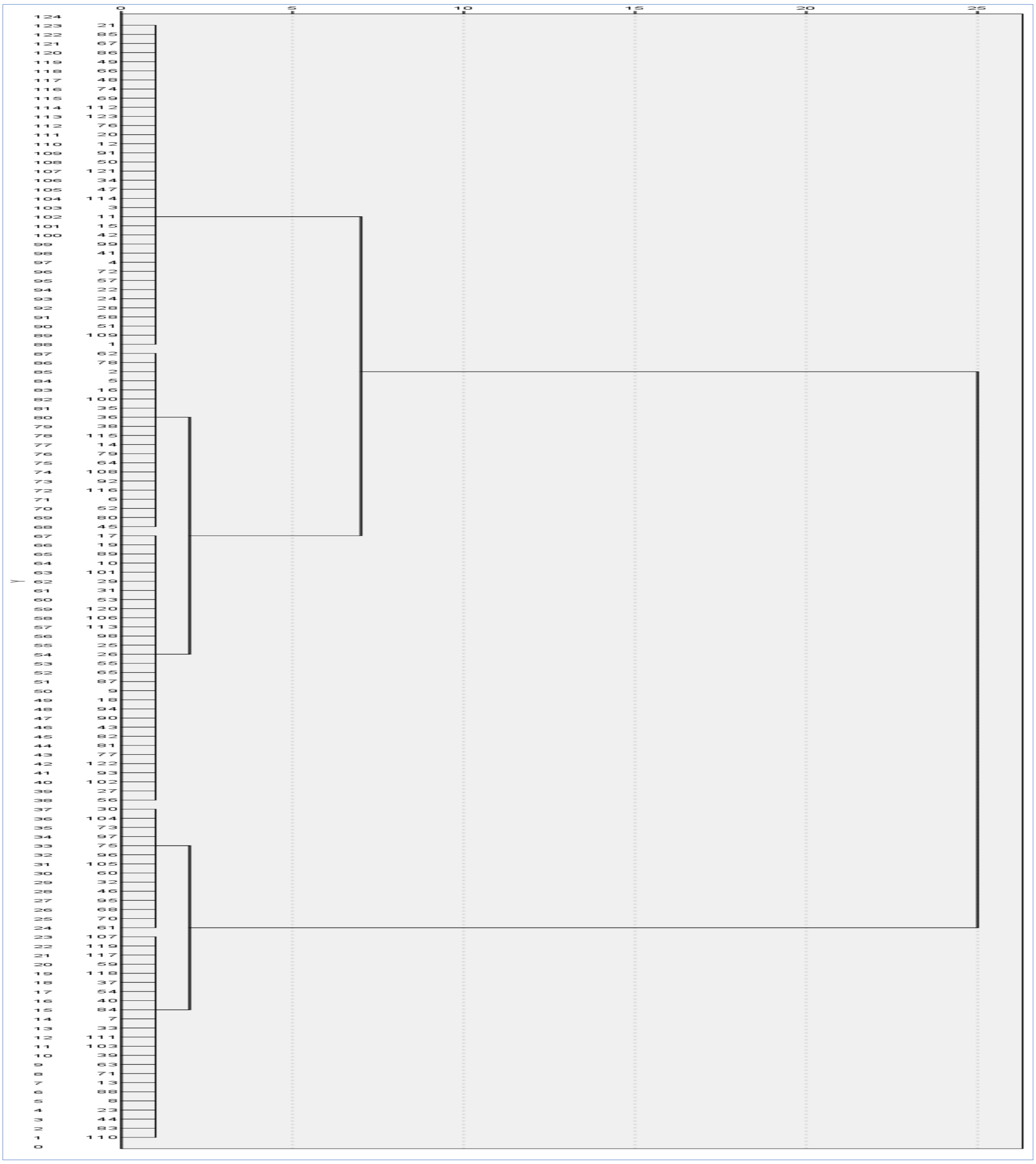

Figure D1. Dendrogram.

Figure D2 presents the Elbow Method used to assess the appropriate number of clusters for the k-means clustering procedure. The plot shows a substantial reduction in the within-cluster sum of squares when moving from three to four clusters, followed by progressively smaller marginal

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improvements for higher values of K. This inflection point indicates that the four-cluster solution achieves a balance between explanatory adequacy and parsimony, as additional clusters yield diminishing returns in terms of within-cluster variance reduction. The Elbow Method thus provides complementary quantitative support for the four-cluster solution identified through hierarchical clustering diagnostics.

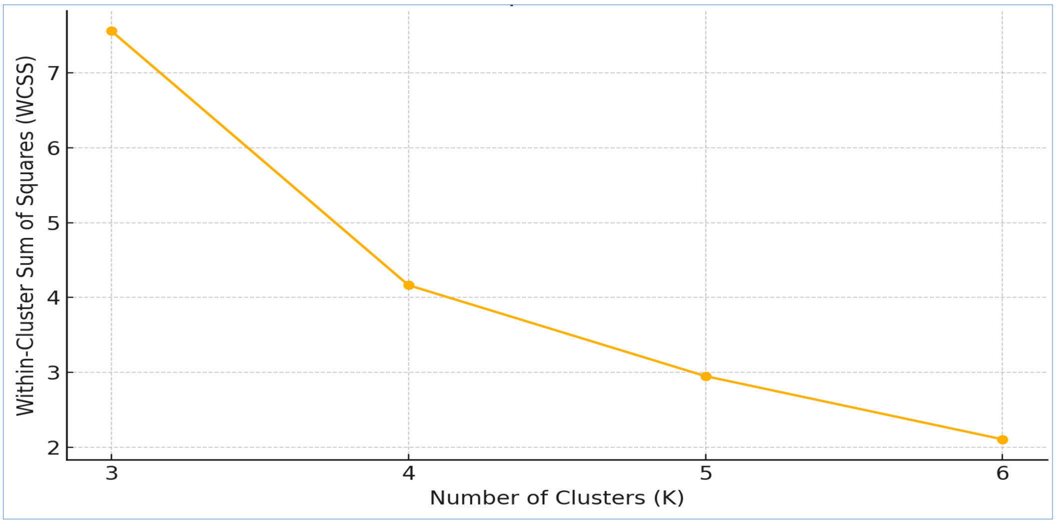

Figure D2. Elbow Method for optimal number of clusters.

Figure D3 presents a scatterplot mapping countries according to their LESG scores and GDP per capita, with observations colored by cluster membership. The horizontal axis reports the normalized LESG index values, while the vertical axis reports GDP per capita. Each point represents a country, and colors correspond to the four clusters identified through the two-stage clustering procedure. The figure provides a cross-sectional visualization of the distribution of countries across systemic development readiness regimes and their associated income levels, without implying causal relationships or dynamic transitions.

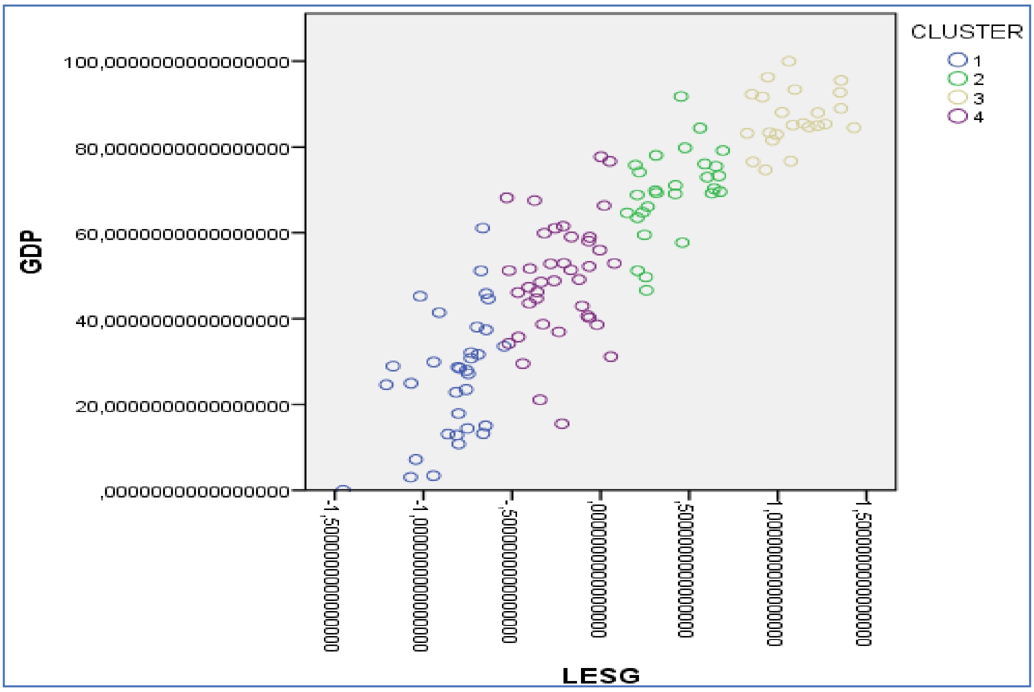

Figure D3. Regression GDP-LESG by cluster.

Tables D5–D8 report the country composition of each systemic development readiness regime, including cluster membership and corresponding LESG scores.

Table D5. Systemically Vulnerable countries (Cluster 1).

Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score
Afghanistan	-1,45	Cameroon	-1,07	Guinea	-0,82	Liberia	-0,80	Sudan	-1,17
Algeria	-0,63	Central African Republic	-1,07	Guinea-Bissau	-0,75	Madagascar	-0,94	Tajikistan	-0,80
Angola	-0,94	Congo, Dem. Rep.	-1,04	Haiti	-1,21	Mali	-0,81	Togo	-0,65
Bangladesh	-0,69	Djibouti	-0,65	Iran, Islamic Rep.	-0,91	Mauritania	-0,80	Uzbekistan	-0,54
Bolivia	-0,70	Gabon	-0,67	Iraq	-1,02	Nicaragua	-0,73	Zimbabwe	-0,81
Burkina Faso	-0,86	Gambia	-0,66	Kyrgyz Republic	-0,75	Nigeria	-0,76		
Cambodia	-0,73	Guatemala	-0,65	Lao PDR	-0,76	Russian Federation	-0,66		

Table D6. Transitional Systems countries (Cluster 4).

Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score
Albania	-0,28	Colombia	-0,12	India	0,06	Mongolia	-0,47	Philippines	-0,02
Argentina	-0,21	Egypt, Arab Rep.	-0,24	Indonesia	-0,10	Montenegro	-0,06	Rwanda	-0,22
Armenia	-0,40	El Salvador	-0,36	Jamaica	-0,26	Namibia	-0,06	Serbia	-0,16
Bahamas, The	0,00	Fiji	-0,36	Kazakhstan	-0,32	North Macedonia	0,08	Sri Lanka	-0,33
Belarus	-0,52	Georgia	-0,06	Kuwait	0,05	Panama	0,02	Trinidad and Tobago	-0,37

Benin	-0,34	Ghana	-0,44	Mauritius	-0,07	Papua New Guinea	-0,52	Ukraine	-0,40
Bosnia and Herzegovina	-0,21	Guyana	-0,53	Mexico	-0,26	Paraguay	-0,41	Vietnam	-0,07
Brazil	0,00	Honduras	-0,46	Moldova	-0,34	Peru	-0,17		

Table D7. Moderate Performers countries (Cluster 2).

Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score
Bahrain	0,22	Croatia	0,42	Italy	0,69	Poland	0,63	Slovenia	0,59
Botswana	0,21	Cyprus	0,31	Latvia	0,67	Portugal	0,60	South Africa	0,26
Bulgaria	0,21	Czech Republic	0,65	Lithuania	0,67	Qatar	0,45	Thailand	0,25
Chile	0,24	Greece	0,64	Malaysia	0,46	Romania	0,27	Uruguay	0,31
China	0,25	Hungary	0,31	Malta	0,48	Saudi Arabia	0,20		
Costa Rica	0,15	Israel	0,56	Oman	0,21	Slovak Republic	0,42		

Table D8. Systemic Leaders countries (Cluster 3).

Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score	Country	LESG score
Australia	1,02	Estonia	0,93	Ireland	0,94	Norway	1,10	United Arab Emirates	0,83
Austria	1,14	Finland	1,43	Japan	1,07	Singapore	1,35	United Kingdom	0,95
Belgium	1,08	France	0,97	Luxembourg	1,06	Spain	0,86	United States	0,85
Canada	1,18	Germany	1,22	Netherlands	1,23	Sweden	1,27		

Denmark	1,36	Iceland	0,91	New Zealand	0,99	Switzerland	1,36

Appendix E. Robustness

Appendix E3. Robustness

This appendix reports a set of robustness checks conducted to assess the sensitivity and reliability of the LESG index with respect to key methodological choices. The robustness analysis is organized into three parts. Appendix E1 examines the sensitivity of the LESG index to alternative aggregation schemes by comparing the baseline PCA-based specification with an equal-weight formulation (LESG_equal). Appendix E2 evaluates the robustness of the underlying factor structure by considering alternative PCA specifications. Appendix E3 assesses the stability of the regime classification through alternative clustering procedures. Together, these checks ensure that the empirical results reflect stable structural patterns rather than artefacts of specific methodological assumptions.

Appendix E1. Equal-Weight Robustness

This section examines the sensitivity of the LESG index to alternative aggregation schemes. Specifically, the baseline PCA-based LESG index is compared with an equal-weight formulation that assigns identical weights to logistics performance, environmental performance, social development, and governance quality. The objective of this exercise is to assess whether the level and ranking of countries are materially affected by the choice of weighting methodology.

Table E1.1 reports descriptive statistics for the baseline PCA-based LESG index and its equal-weight counterpart. As expected, the two indices differ in scale and distribution due to their distinct aggregation procedures. The PCA-based LESG index is standardized, with a mean of zero and a symmetric range spanning from −1,45 to 1,43, reflecting its construction as a latent composite score. In contrast, the equal-weight LESG index is expressed on a 0–100-type scale, with values ranging from 29,27 to 80,90 and a mean of 55,14, capturing average performance across the four constituent dimensions. Importantly, both indices are computed on the same sample of 123 countries, ensuring full comparability in subsequent robustness assessments. The descriptive statistics indicate substantial cross-country variation under both specifications, suggesting that the equal-weight formulation preserves meaningful dispersion and does not mechanically compress country differences.

Table E1.1. Descriptive Statistics.

	N	Minimum	Maximum	Mean	Std. Deviation
LESG	123	-1,45	1,43	0,000	0,707
LESG_equal	123	29,27	80,90	55,139	12,419

Table E1.2 reports rank-based correlation coefficients between the baseline PCA-based LESG index and the equal-weight formulation. The results indicate a very strong and statistically significant association across all non-parametric measures. Spearman's rho reaches 0,979 ($p < 0,01$), while Kendall's tau-b equals 0,885 ($p < 0,01$), reflecting a high degree of concordance in country rankings under the two aggregation schemes.

Table E1.2. Correlations.

			LESG	LESG_equal
Kendall's tau_b	LESG	Correlation Coefficient	1,000	0,885**
		Sig. (2-tailed)	.	0,000
		N	123	123
	LESG_equal	Correlation Coefficient	0,885**	1,000
		Sig. (2-tailed)	0,000	.
		N	123	123
Spearman's rho	LESG	Correlation Coefficient	1,000	0,979**
		Sig. (2-tailed)	.	0,000
		N	123	123
	LESG_equal	Correlation Coefficient	0,979**	1,000
		Sig. (2-tailed)	0,000	.
		N	123	123

**. Correlation is significant at the 0.01 level (2-tailed).

The use of rank-based correlations is particularly appropriate given the different scaling and distributional properties of the two indices. The consistently high coefficients suggest that the relative positioning of countries is largely preserved when moving from variance-based PCA weights to equal weighting, indicating that the LESG index captures a stable underlying structure rather than being driven by specific weighting choices.

Overall, the robustness check based on alternative weighting schemes confirms that the LESG index is not sensitive to the choice between PCA-derived and equal weights. Despite differences in scale and construction, both formulations yield highly consistent country rankings. This finding supports the interpretation of LESG as a structurally grounded measure of systemic readiness rather than an artefact of a particular aggregation rule.

Appendix E2.: Robustness of the PCA Structure

This section examines the robustness of the LESG index with respect to the underlying principal component structure. Specifically, alternative PCA specifications are considered to assess whether the dimensional composition and relative importance of the extracted components remain stable across reasonable methodological choices. The objective is to verify that the LESG index reflects a persistent latent structure rather than being sensitive to a particular extraction or rotation setting.

The Kaiser–Meyer–Olkin (KMO) (Table E2.1) measure of sampling adequacy equals 0.826, indicating a high degree of common variance among the variables and confirming the suitability of the dataset for factor-based analysis. Bartlett's test of sphericity is statistically significant ($\chi^2 = 378{,}548$, df = 6, $p < 0.001$), rejecting the null hypothesis of an identity correlation matrix. Together, these diagnostics provide strong empirical support for the application of Principal Component Analysis in examining the underlying structure of the LESG dimensions.

Table E2.1. KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0,826
Bartlett's Test of Sphericity	**Approx. Chi-Square**	378,548

	df	6
	Sig.	0,000

Table E2.2 reports the eigenvalue structure and explained variance of the principal component analysis underlying the LESG framework. The results indicate a clearly dominant first component, with an eigenvalue of 3,251, accounting for 81,27% of the total variance. This substantially exceeds the Kaiser threshold and suggests the presence of a strong common latent dimension underlying the four LESG pillars.

Table E2.2. Total Variance Explained.

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	3,251	81,268	81,268	3,251	81,268	81,268
2	0,362	9,054	90,323			
3	0,231	5,770	96,092			
4	0,156	3,908	100,000			

All remaining components exhibit eigenvalues well below unity and contribute marginally to the explained variance, collectively accounting for less than 19% of total variation. The sharp drop after the first component is consistent with a one-dimensional structure, supporting the interpretation of LESG as a unified measure of systemic readiness rather than a multi-factor construct.

Table E2.3 presents the unrotated component loadings for the single principal component retained in the LESG framework. All four dimensions—logistics performance (LPI), environmental performance (EPI), social development (SDG), and governance quality (WGI)—exhibit very high and positive loadings on the first component, ranging from 0.885 to 0.933. As only a single component is extracted, rotation is not applicable and the rotated solution coincides with the unrotated component structure. This outcome is consistent with the eigenvalue and scree plot results, which indicate a strongly dominant first component and no meaningful secondary dimensions.

Table E2.3. Component Matrix.

	Component
Variables	1
LPI	0,885
EPI	0,895
SDG	0,892
WGI	0,933

The scree plot (Figure E2.1) exhibits a pronounced elbow after the first component, with a sharp decline in eigenvalues and a clear flattening of the curve thereafter. This pattern indicates that only the first component contributes substantively to the explained variance, while subsequent components represent marginal and unsystematic variation. The visual evidence from the scree plot therefore corroborates the eigenvalue criterion and the component loading structure, reinforcing the conclusion that the LESG framework is characterized by a single dominant latent dimension.

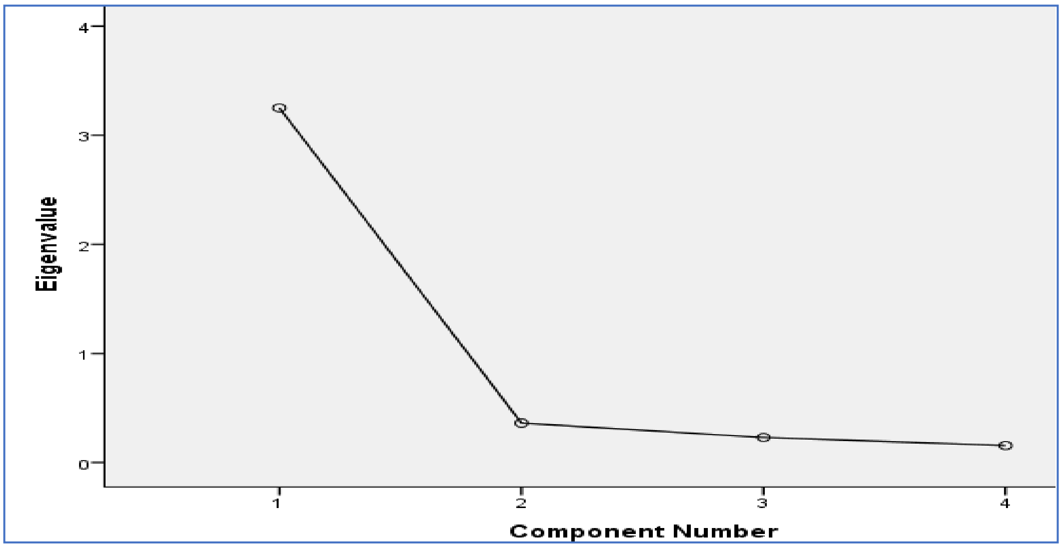

Figure E2.1. Scree Plot.

The robustness checks confirm that the PCA structure underlying the LESG index is highly stable. A single dominant component explains more than 80% of total variance, and all four constituent dimensions load strongly and uniformly on this component. Alternative PCA specifications yield identical structural outcomes, indicating that the LESG index reflects a well-defined latent construct rather than being sensitive to extraction or rotation choices. These results support the interpretation of LESG as a coherent and internally consistent measure of systemic development readiness.

Appendix E3. Robustness of the Cluster Structure

In contrast to the PCA robustness checks, which focus on the internal structure of the index, this section evaluates the stability of the external regime classification derived from the LESG scores. Alternative clustering specifications are considered to assess whether the identified systemic development regimes remain stable under reasonable methodological variations. The objective is to verify that the observed cluster structure reflects persistent patterns in systemic readiness rather than being an artefact of a specific clustering algorithm or parameter choice.

To assess the robustness of the regime structure, a k-means cluster analysis was conducted using the LESG index with the number of clusters set to three. The resulting final cluster centers (Table E3.1) exhibit a clear monotonic ordering, with Cluster 1 characterized by a negative centroid (−0,73), Cluster 2 centered around near-zero values (0,04), and Cluster 3 displaying a strongly positive centroid (0,96). This configuration confirms that the LESG index consistently differentiates countries into low-, intermediate-, and high-readiness regimes even under alternative clustering specifications. The persistence of ordered and well-separated cluster centers supports the structural stability of the regime-based classification.

As an additional robustness check, the k-means clustering procedure was repeated with the number of clusters increased to five. The resulting final cluster centers (Table E3.2) remain strictly ordered along the LESG dimension, ranging from −1,08 to 1,09. Compared to the three-cluster solution, the five-cluster specification does not alter the overall hierarchical structure of systemic readiness, but instead provides a finer partitioning of low and intermediate regimes. High-readiness countries remain clearly separated, while lower-readiness countries are subdivided into more granular vulnerability and transition categories. This result confirms that the regime structure identified by the LESG index is stable to alternative clustering specifications and is not driven by an arbitrary choice of the number of clusters.

Table E3.1. Final Cluster centers (3 clusters).

	Cluster		
	1	2	3
LESG	-0,73	0,04	0,96

Hierarchical clustering using Ward's linkage and squared Euclidean distance was employed as an additional robustness check to examine the underlying grouping tructure of the LESG index. The resulting dendrogram (Figure E3.1) reveals pronounced jumps in rescaled distance at higher levels of aggregation, indicating the presence of a limited number of structurally distinct clusters rather than a continuous distribution. In particular, the largest increase in fusion distance occurs between three and four clusters, suggesting that solutions in this range best capture the latent regime structure of systemic development readiness. This hierarchical evidence supports the subsequent k-means specifications and confirms that the identified regimes are not artifacts of the clustering algorithm but reflect genuine structural differentiation in LESG profiles.

Although alternative cluster solutions were examined for robustness, the four-cluster specification is retained as the main analytical result. Hierarchical clustering using Ward's method reveals a pronounced increase in fusion distance between three and four clusters, indicating that this partition best captures the latent regime structure of the LESG index. Compared to the three-cluster solution, the four-cluster specification preserves meaningful differentiation between transitional and moderate-readiness systems, while avoiding the over-fragmentation observed in higher-order solutions. The resulting regimes exhibit clear monotonic ordering in LESG scores and distinct structural profiles, enhancing interpretability and policy relevance. Accordingly, the four-cluster solution is adopted as the preferred classification of systemic development readiness regimes.

Table E3.2. Final Cluster centers (5 clusters).

	Cluster				
	1	2	3	4	5
LESG	-1,08	0,40	-0,18	-0,68	1,09

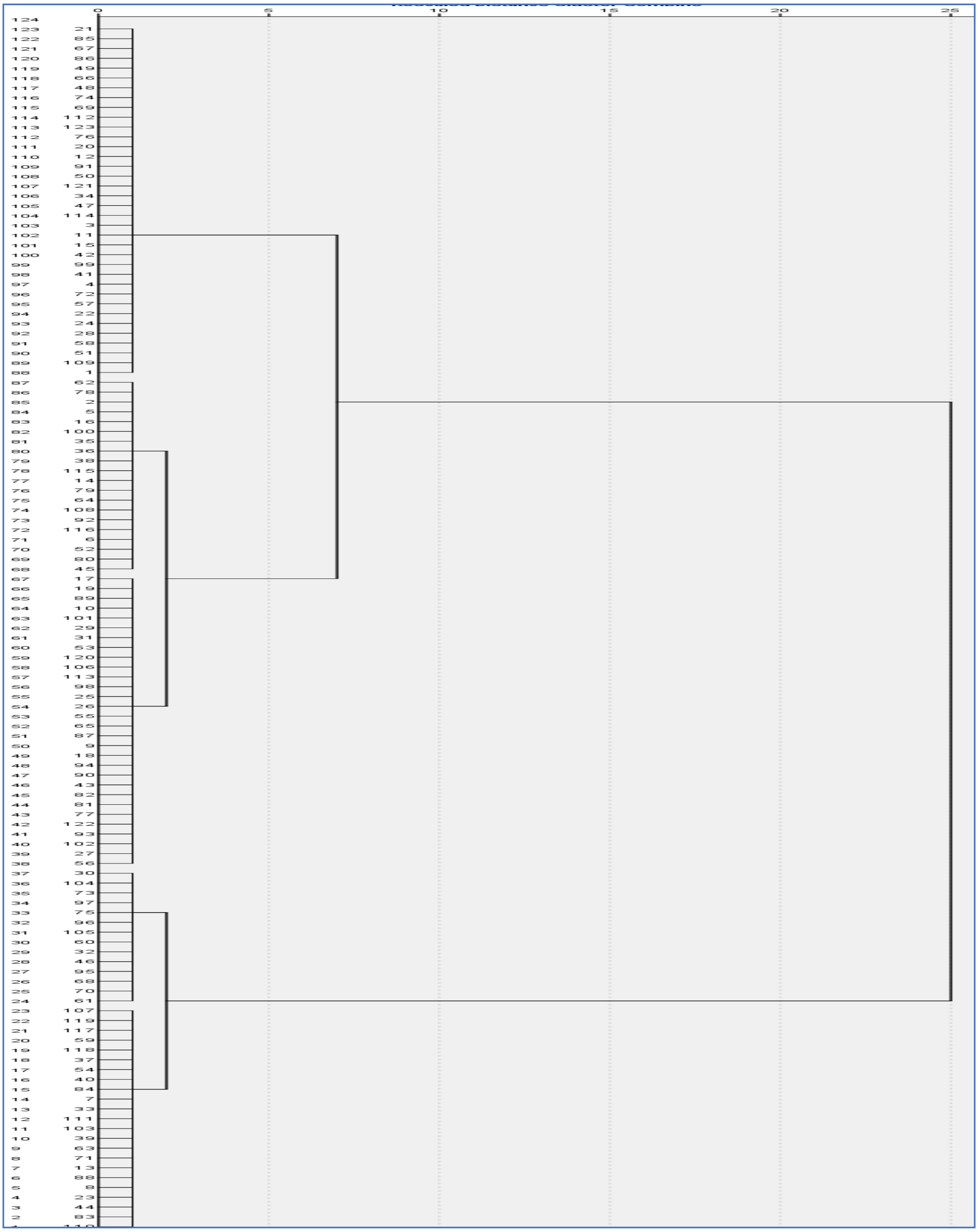

Figure E3.1. Dendrogram.

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