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An Enhanced Composite Green Logistics Performance Index for MENA: Methodology, Drivers and Hybrid Forecasting to 2030

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Abstract

Background: Amid rising trade, urbanization, and carbon emissions in MENA countries, sustainable logistics faces major constraints. This study develops an enhanced Green Logistics Performance Index (GLPI) using min-max normalization and Principal Component Analysis (PCA) to integrate the World Bank's Logistics Performance Index (LPI) and Yale's Environmental Performance Index (EPI). The study uses fixed-effects panel regression on data from 20 MENA countries (2018–2024), identifies key drivers, and applies ARIMA and LSTM models for 2030 projections. The prior ratio-based GLPI suffered from scale sensitivity and volatility; this refined version provides improved stability and predictive utility for Green Supply Chain Management (GSCM). *Methods:* Panel data from 20 MENA countries (2018–2024) were analyzed. The enhanced GLPI normalizes and weights LPI and EPI scores via PCA. Fixed-effects regression identifies drivers, while ARIMA and LSTM enable scenario-based forecasting (baseline, optimistic, and pessimistic). *Results:* Renewable energy share positively influences GLPI, while trade openness has a negative effect. Projections indicate the regional GLPI will reach about 0.65 by 2030, with Saudi Arabia potentially achieving 25% higher under optimistic conditions. *Conclusions:* The refined GLPI advances GSCM theory by operationalizing triple bottom line trade-offs through a robust, predictive metric. It bridges descriptive limitations in prior literature, enabling forward-looking insights into sustainable logistics in emerging economies, with potential applicability beyond MENA.

Keywords: green logistics performance index; supply chain; MENA; LPI and EPI

1. Introduction

The Middle East and North Africa (MENA) region occupies a strategic position at the crossroads of global trade via major maritime corridors such as the Suez Canal and the Strait of Hormuz. The aspiration for sustainable logistics development in the region is challenged by several factors. Examples include rapid urbanization. In many countries, the population growth exceeds 2% a year. The high dependence on hydrocarbon exports leads to associated problems including water scarcity, in addition to considerably high CO_2 emissions leading to poor air quality from the transportation sector. As a result, the transport and logistics sector is expected to remain a significant regional source of greenhouse gas emissions in 2025, with road freight and maritime shipping activities representing the primary sources. This issue is further intensified by the rapid development of e-commerce and the ongoing

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economic diversification initiatives, which intensify the existing environmental problems of this region [1].

The LPI, a well-respected periodic benchmark established by the World Bank and most recently published in 2023, measures and compares countries across six important dimensions: customs procedures, infrastructure quality, ease-of-arranging shipments, quality of logistics services, ability to track and trace consignments, as well as punctuality of transport services [2]. Across these dimensions, performance varies significantly across countries in the Arab region, and the United Arab Emirates (UAE) stands out as one of the world's top performers due to large investments made in world-class deep-sea ports like Jebel Ali and innovative digital platforms that facilitate more efficient logistics operations. In line with this approach, the EPI of Yale University compares countries using an overall environmental performance score based on 58 indicators that have been carefully selected and aggregated into eleven sub-components from relevant areas such as climate change mitigation or the health of vital ecosystems [3]. The UAE is also the MENA leader with a high score of around 51.6, closely followed by Oman. This is in clear contrast to the regional median score of 43.2, which lags well below the average levels of action around the world and highlights substantial deficiencies across all aspects of climate action, particularly in countries with conflict or instability issues.

Early attempts to integrate logistics performance and environmental aspects, such as MENA specific GLPI from 2014 [4], as well as other existing global suggestions on a more general level [5], resorted mainly to basic ratio-based methods (e.g., an equation like GLPI = LPI/EPI). These two initial approaches had some methodological limitations: in particular, their strong scale sensitivity because of the non-equivalent scales of the LPI (from 1 to 5) and EPI (from 0 to 100). In addition, these methods showed an evident lack of normalization combined with a lack of systematic weighting which yielded an inconsistent output and reduced comparability. This limitation is problematic in the significantly heterogeneous MENA region, as extreme scores, particularly those from conflict areas, may distort evaluations excessively. Such structural deficiencies severely constrain the practical applicability of these early approaches for conducting robust comprehensive assessments regarding eco-efficiency and sound policy recommendations in the field of GSCM [4].

Therefore, this research is motivated by the need to address such well-documented limitations as noted in existing literature and contributes significantly to both theory and method in the field of GSCM specifically within an emerging region [6]. Through using the min-max normalization method to standardize both indices into a unified [0, 1] scale, together with the sophisticated application of PCA for data-driven weighting, the improved GLPI attains a stability that is significantly higher, a volatility that is much lower and an enhanced potential to be compared between countries, which are essential for robust analysis [7]. The inclusion of fixed-effects panel regression here in driver analysis, coupled with state-of-the-art hybrid machine learning forecasting techniques, namely ARIMA for linear trend capturing and LSTM networks for non-linear feature exploration, represents a predictive capacity that was missing from past descriptive research. The key contributions of these developments are in largely bridging the theoretical limitations that emerge from the present GSCM literature, specifically being that combined indices too often fail to balance efficient operations against environmental performance and broader sustainability objectives [8]. These advancements enable the generation of forward-looking insights which are imperative for designing the logistics systems necessary for sustainable development considering the accelerating urban expansion and ever-increasing decarbonization demands that define the contemporary world [9,10].

This study adopts a sequential and integrated methodological framework. First, Principal Component Analysis (PCA) is employed to construct a statistically weighted composite

Green Logistics Performance Index (GLPI). Second, fixed-effects panel regression identifies macroeconomic and environmental determinants of GLPI, addressing the research question concerning drivers of green logistics performance. Third, ARIMA and LSTM forecasting models are implemented to project GLPI trajectories to 2030 under alternative policy scenarios. Thus, PCA serves index construction, panel regression explains determinants, and hybrid forecasting provides predictive policy insight. The methods are complementary rather than fragmented.

The research question addressed in this study is as follows. How can green logistics performance in MENA be measured more robustly and forecasted more usefully for policy design than previous ratio-based approaches? The purpose of this study is to develop and validate an enhanced composite GLPI, identify its macro-level drivers, and project its trajectory to 2030 under alternative scenarios. This study makes three contributions to the literature. From a theoretical perspective, this links green logistics measurement to GSCM, NRBV, Institutional Theory and ecological modernization logic through operationalization of the efficiency–ecological performance trade-off in logistics. Empirically, it proposes a normalized and PCA-weighted GLPI for MENA and tests its determinants through fixed-effects panel regression. In policy terms, it offers scenario-based forecasts and a tool for diagnostics in prioritizing renewable integration, trade facilitation reform and investment in green logistics. The remainder of the paper is organized as follows. Section 2 presents the theoretical background and literature review. Section 3 explains the conceptual framework, data, and methods, including index construction, panel regression, and forecasting. Section 4 reports empirical and forecast results and links the findings to prior literature. Section 5 concludes with implications, policy recommendations, limitations, and future research directions.

2. Theoretical Background and Literature Review

2.1. Green Supply Chain Management and Sustainable Logistics in MENA Countries

The GSCM model adopts the concept of sustainable development into conventional supply chains to obtain eco-advantages as well as cost and time-effectiveness [11]. Being based on the concept of sustainable development, GSCM covers different areas such as inverse logistics, ecological design, green purchasing and low-carbon transportation to achieve economic, environmental and social benefits [12].

Theoretically, this study draws on the Natural Resource-Based View (NRBV) [13], which argues that firms can achieve competitive advantage through environmentally sustainable practices, extending this to macro-level logistics in MENA. It also involves Institutional Theory [13], highlighting how regulatory inconsistencies and oil dependency create institutional pressures that hinder GSCM adoption [14,15]. By refining the GLPI, these theoretical tensions are addressed, enabling empirical testing of dynamic capabilities for green transitions in emerging contexts [16]. Green logistics focuses on ecological impact reduction, for instance route optimization, transfer to rail or water transport, use of electric vehicles and energy efficiency within warehouses [17]. In the MENA region, numerous structural and environmental challenges persist such as high temperature, rapid urbanization, non-renewable energy sources and urban development which significantly rely on road transportation due to insufficient and underdeveloped rail infrastructure. Moreover, the region faces severe desertification and water shortages which further constrain sustainable economic and logistical development. The MENA region's position as a crossroads between Europe, Asia and Africa does offer prospects of development of sustainable trade transitions [18]. Recent research provides evidence of GSCM implementation and that eco-practices enhance the quality services in Egypt [19] and infrastructure facilitates customer satisfaction in Saudi Arabia [20].

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In addition, the study also relies on Ecological Modernization Theory (EMT), which posits that environmental improvements can emerge from economic activity through technological innovation, institutional reform and industrial upgrading rather than from growth inhibitions alone. EMT matters for MENA logistics because the region's green transition relies on cleaner transport technologies, digital logistics systems, renewable energy expansion and regulatory modernization. This study elaborates on NRBV and Institutional Theory by employing a macro theory (EMT) that explains how at the macro level, policy reform and technology adoption can enhance both logistics capability as well as environmental outcomes where each is interdependent over time.

GSCM is critical in reducing oil dependency, especially within Saudi Vision 2030, which achieved significant progress toward its strategic objectives (approximately 85% of targeted milestones) including commitments to green infrastructure and digitalization initiatives. However, the high cost of green technologies and lack of consistency in regulation [21,22], as well as a gap between the Gulf and North Africa, remain an obstacle to the standard adoption of GSCM practices [22]. This project has a strong connection to Sustainable Development Goals (SDGs) 9 and 13 on industry innovation and infrastructure, and climate action, respectively.

2.2. Logistics Performance Index

The World Bank's LPI measures trade logistics performance among 139 countries and comprises six main dimensions including customs clearance, infrastructure quality, ease of arranging transported shipments, competence and quality of logistics services, ability to track and trace consignments up to the receiving firms' door, and timeliness [23]. For the 2023 edition, big data has been implemented for shipment tracking and there is a renewed emphasis on resilience post COVID-19 [24]. As of 2025, there has been no subsequent release. Performance varies across the MENA region; for example, the UAE is seventh globally in part due to its multimodal hubs including Jebel Ali. Oman along with Qatar have drastically improved, and countries in North Africa such as Morocco and Egypt are determined to improve trade facilitation. At the other end of the spectrum, countries like Iraq and Yemen still face significant infrastructure challenges. The regional LPI should be considered as growing since 2018 due to the Gulf states' investments in logistics, but it remains below global average values, which justifies the importance of integrating sustainability into logistics. The current emphasis is on operational efficiency (without explicit sustainability issues), and therefore, green metrics should be added to attain international goals [24]. Table 1 presents a comparison of MENA countries' 2023 LPI scores and the status of their performance since 2018, as well as highlights about the logistics performance in each country.

2.3. The Environmental Performance Index

A prominent example covering a combination of these various aspects is that of the Environmental Performance Index, a policy-relevant ranking which is published based on sound statistical methods by the reputable academic institutions at Yale and Columbia Universities. It has gained importance since its start in 2006 [25]. All 180 countries are ranked across 11 key indicators from climate mitigation and air quality to biodiversity. As of 2024, Estonia ranks first globally in this index [26]. By examining the MENA region, it was found that the median score is relatively low at 43.2, suggesting the presence of climate-related problems and pollution [27]. Within the regional context, the UAE records one of the highest scores (51.6), and ranking second in the MENA is Oman with (51.3). The strong performance of both countries is due to their ambitious renewable energy and sophisticated desalination programs [28].

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Table 1. MENA Countries-LPI Scores (2023) and change from (2018).

Country	2023 Score	Global Rank (2023)	2018 Score	Global Rank (2018)	Change (2018–2023)	% Change	Notes
UAE	3.94	7	3.96	11	−0.02	−0.5%	Global top performer; minor dip due to post-COVID adjustments
Oman	3.62	28	3.20	43	+0.42	+13.1%	Strong infrastructure gains from Duqm Port investments
Israel	3.60	26	3.31	37	+0.29	+8.8%	Tech-driven logistics improvements; strong in tracking and competence
Qatar	3.59	30	3.47	30	+0.12	+3.5%	Qatar Airways logistics boost; stable rank with aviation focus
Bahrain	3.57	32	2.93	59	+0.64	+21.8%	Steady improvement in Bahrain International Airport expansions
Saudi Arabia	3.53	38	3.01	55	+0.52	+17.3%	Vision 2030 reforms; major gains in timeliness and infrastructure
Egypt	3.35	57	2.82	67	+0.53	+18.8%	Major trade facilitation reforms; Suez Canal enhancements
Morocco	3.31	61	2.54	109	+0.77	+30.3%	Port and rail upgrades; Tanger Med port driving growth
Kuwait	3.20	51	2.86	63	+0.34	+11.9%	Moderate progress in customs; oil logistics focus
Jordan	3.15	75	2.69	84	+0.46	+17.1%	Moderate progress; focus on Aqaba port and regional trade
Tunisia	2.95	91	2.57	105	+0.38	+14.8%	Gradual improvement in shipments; economic recovery efforts
Lebanon	2.89	97	2.72	79	+0.17	+6.3%	Political and economic crisis impacting infrastructure
Algeria	2.78	107	2.45	117	+0.33	+13.5%	Limited progress; focus on port modernization
Iraq	2.70	114	2.18	147	+0.52	+23.9%	Conflict-related constraints; gradual rebuilding
Sudan	2.40	115	2.43	121	−0.03	−1.2%	Instability hindering logistics; minimal change
Libya	1.90	138	2.11	154	−0.21	−10.0%	Severe infrastructure damage from conflict
Yemen	2.20	138	2.27	140	−0.07	−3.1%	Ongoing conflict impact; humanitarian logistics challenges
Iran	2.30	123	2.85	64	−0.55	−19.3%	Sanctions and economic pressures causing decline
Syria	2.30	123	2.30	138	+0.00	+0.0%	Stagnation due to prolonged conflict
Palestine	N/A	N/A	N/A	N/A	N/A	N/A	Not ranked; data limitations due to status and access issues

Notes: Scores on 1–5 scale. % change = (2023 − 2018 score)/2018 × 100. Countries sorted by descending 2023 score. Some scores and ranks approximated based on available data. N/A for countries not ranked in reports. Palestine not included in LPI surveys.

Saudi Arabia achieves a score of 42.5, largely due to its green projects outlined in its Vision 2030 roadmap [28]. For countries affected by conflicts, i.e., Iraq (30.3) and Djibouti (32.3), stagnation or decrease in the score can also be observed. Although there are some indications of a shift to renewable energy sources in the Gulf region, there are still clear gaps in efficient policy mechanisms solving climate problems [29]. These dynamics underline the urgent need for comprehensive policies that effectively interface environmental performance with sectors such as transportation and logistics to promote sustainable development principles [30]. It is notable that methodological changes in scoring processes from one year of an annual release to the next can have large impacts on results, making comparisons across different model years difficult without further detail about how score differences impact performance relative to environmental care or condition among various states [31,32]. Table 2 provides the comparative rank of MENA countries in terms of EPI scores by 2024 indicating the deviation from those recorded in 2018.

Table 2. MENA Countries—EPI Scores (2024) and change from (2018).

Country	2024 Score	Global Rank (2024)	2018 Score	Global Rank (2018)	Change (2018–2024)	% Change	Notes
UAE	51.6	53	58.90	77	−7.3	−12.4%	Decline in rank despite renewable advances
Oman	51.3	55	51.32	116	−0.02	−0.0%	Stable performance with desalination focus
Israel	48.0	70	75.01	19	−27.01	−36.0%	Significant drop, possibly due to regional factors
Jordan	47.3	77	62.20	62	−14.90	−24.0%	Decline amid water stress challenges
Qatar	46.8	82	67.80	32	−21.00	−31.0%	Sharp fall despite aviation investments
Tunisia	45.3	91	62.35	58	−17.05	−27.3%	Gradual decline with pollution concerns
Kuwait	44.4	95	62.28	61	−17.88	−28.7%	Oil economy struggles with emissions
Egypt	43.7	101	61.21	66	−17.51	−28.6%	Challenges in air quality and water
Saudi Arabia	42.5	108	57.47	86	−14.97	−26.0%	Improvement trend via Vision 2030 greens
Iran	41.8	113	58.16	80	−16.36	−28.1%	Sanctions impacting environmental efforts
Algeria	41.7	114	57.18	88	−15.48	−27.1%	Limited progress in biodiversity
Lebanon	39.9	126	61.08	67	−21.18	−34.7%	Crisis-driven decline in ecosystem vitality
Morocco	39.5	128	63.47	54	−23.97	−37.8%	Port upgrades but pollution issues
Sudan	39.1	131	51.49	115	−12.39	−24.1%	Instability affecting climate mitigation
Bahrain	35.3	157	55.15	96	−19.85	−36.0%	High emissions from urbanization
Iraq	30.3	172	43.20	152	−12.90	−29.9%	Conflict exacerbating pollution
Libya	N/A	N/A	49.79	123	N/A	N/A	Data unavailable due to instability
Syria	N/A	N/A	N/A	N/A	N/A	N/A	Not ranked; ongoing conflict
Yemen	N/A	N/A	N/A	N/A	N/A	N/A	Not ranked; humanitarian crisis
Palestine	N/A	N/A	N/A	N/A	N/A	N/A	Not ranked; data limitations

Notes: Scores on 0–100 scale. % change = (2024 − 2018 score)/2018 × 100. Countries sorted by 2024 scores descending. Some 2018 ranks adjusted for consistency. N/A for countries not ranked in reports. Palestine often not separately ranked; may be included under other categories in some data.

2.4. Composite Green Logistics Performance Index

Composite indices are an aggregation of indicators into a single value and used for comparability across countries in terms of economic and environmental performance [33,34]. Although, initial approaches for GLPI in MENA have been pursued with some methodological constraints which compromised their robustness and generalizability in diverse areas such as MENA.

The original version of the GLPI in 2011 [35] and recalibrated for MENA [36] had methodological challenges such as scale dependence. Improved versions use normalized composites and PCA weights for accuracy. Several international studies [37,38] expect that increasing LPIs lead to smaller ecological footprints. The UMAP and K-means can uncover the multidimensional structures in the MENA region [37]. System efficiency is the formulation of economic and ecological objectives, and with ML techniques, proactive forecasting can be used [39]. In addition, advanced predictions in the logistics area may create predictive composites predictively with the help of machine learning algorithms for proactive trend analysis and decision support that serve planning logistics [40]. The use of an advanced GLPI-MENA formula applied to the MENA region, shown in the table below, is a new method based on normalized LPI scores in 2023 and EPI scores from 2024 [41]. The adjusted Green Logistics Performance Index (GLPI, 2023–2024) of MENA Countries is provided in Table 3.

Table 3. Enhanced MENA Countries Green Logistics Performance Index (GLPI).

Country	LPI 2023	EPI 2024	GLPI
UAE	3.94	51.6	1.000000
Oman	3.62	51.3	0.895397
Israel	3.60	48.0	0.811834
Qatar	3.59	46.8	0.780617
Saudi Arabia	3.53	42.5	0.661385
Jordan	3.15	47.3	0.658207
Egypt	3.35	43.7	0.634676
Kuwait	3.20	44.4	0.605376
Tunisia	2.95	45.3	0.550283
Morocco	3.31	39.5	0.523889
Bahrain	3.57	35.3	0.504566
Algeria	2.78	41.7	0.413947
Lebanon	2.89	39.9	0.405230
Iran	2.30	41.8	0.269953
Sudan	2.40	39.1	0.237061
Iraq	2.70	30.3	0.121951
Libya	1.90	N/A	N/A
Yemen	2.20	N/A	N/A
Syria	2.30	N/A	N/A
Palestine	N/A	N/A	N/A

Notes: GLPI on [0, 1] scale; higher values indicate better green logistics performance. N/A for countries with insufficient data. Sorted by descending GLPI.

In sustainable logistics and supply chains, the process of statistical forecasting transforms descriptive analysis into predictive inference for policy in dynamic settings. ARIMA model addresses trends linear while ML methods such as LSTMs manage non-linearity. In logistic applications, machine learning (ML) enhances demand forecast leading to cost and emission savings. The hybrid models provide better performance than the pure forms in terms of supply chain efficiency [42]. It performs well in sequential data on inventory risk and disruption risk [43]. XGBoost has been used in Environmental, Social and Governance (ESG)-related prediction tasks. Prediction models remain at the early stage but are progressing in MENA for Vision 2030 logistics. Some global studies forecast decarbonization in developing countries [44]. For MENA and Saudi predictions in this study, PCA-weighed with ARIMA and LSTM are employed.

2.5. Prior Approaches to Composite Green Logistics Indices and Research Gaps

The literature reviews show that there is a gap in proposing a comprehensive method for constructing composite indices of environmental performance and logistics efficiency. For example, the next generation of such adaptations, e.g., in MENA settings [4,43], defined a simple GLPI as LPI divided by EPI step to make the ratio of GLPI = LPI/EPI. This methodology attempted to determine if countries are efficient in logistics (i.e., at the cost of reducing environmental quality) but was affected by several limitations. Significant methodological issues in these prior studies are:

- High-scale sensitivity due to mismatched ranges (LPI: 1–5; EPI: 0–100), causing minor changes in EPI to disproportionately affect the ratio and produce volatile results, especially in regions with extreme score variations (e.g., conflict-affected MENA countries).
- Lack of normalization, which prevents fair comparability across indicators and countries.
- Absence of systematic weighting, often resulting in implicit equal weighting or arbitrary ratios that fail to reflect underlying data structures or relative importance.
- Limited predictive capability, with most studies remaining descriptive and lacking integration of forecasting models for policy-oriented insights.

These limitations undermine the robustness, stability and practical applicability of first-generation GLPI builds for cross-country comparison for sustainable logistics in complex developing economies. To address these shortcomings, this study proposes a new and improved GLPI framework incorporating two methodological advances based on the theory of composite index:

- Min-max normalization scales both LPI and EPI to a common [0, 1] range, correcting for scale discrepancies and stabilizing the index (such as lessening volatility), making it more suitable for cross-country comparison, a routine procedure in sound composite indicator building processes, e.g., OECD guidelines; JRC handbook on composite indicators.
- PCA for data-driven weighting is used to identify underlying patterns in the normalized data and reflect the actual weights discovered from the variance explained (for example, loadings of first principal component) rather than that assumed or equal. PCA increases objectivity, eliminates problems with dimensionality, and provides weight, reflecting the informational content of the indicators, an oft-cited method for composite sustainability indices in economy, environmental studies, and GSCM, e.g., uses in sustainability indicators, and product market regulation indices.

In several ways, these refinements extend our understanding of sustainable supply chains and GSCM:

- Better cross-regional comparison becomes viable, preserving reliable benchmarking attitudes across considerably diverse environments (the Gulf vs. North African countries).
- Inclusion of predictive modeling (by using ARIMA and LSTM forecast) takes the index beyond a static description and facilitates proactive policy analysis, to account for potential dynamic trends in decarbonization, trade growth and urbanization—an under-researched domain in MENA-focused sustainable logistics literature.

Empirical support is provided for the triple bottom line in GSCM practices by deploying a balanced and stable metric that connects performance (economic pillar) with environmental impact, which could inspire further research on green transitions in hydrocarbon-based and emerging economies. Accordingly, Table 4 shows a comparison between GLPI approaches and the proposed technique.

Table 4. Comparison of prior GLPI approaches vs. proposed methodology.

Approach	Method	Key Limitations	Theoretical Advancement
Prior Ratio-Based [4,34]	Simple LPI/EPI ratio	Scale sensitivity, volatility, no normalization/weighting	Limited; descriptive, ignores TBL trade-offs
Proposed Enhanced GLPI	Min-max normalization + PCA weighting + hybrid forecasting	Addresses volatility; adds predictive capability	Advances GSCM by operationalizing TBL through data-driven metrics; enables testing of NRBV and Institutional Theory in emerging contexts

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Recent research bolsters the argument for a more nuanced, rigorous gap statement. Applying a similar logic, recent framework-based logistics scholarship identifies salient logistics performance indicators and their structural relationships for the analysis of economic growth [44] but does not construct a composite green logistics index that would balance environmental outputs with logistics performance in a comparable cross-country dimension nor analyze which panel determinants were at work through MENA [45]. Simultaneously, the recent hybrid modeling works in the energy domain demonstrate on a policy level the value of scenario-based forecasting under decarbonization transitions; however, those methods are not imported into the data-driven conventional composite green logistics performance framework [46]. Drawing on this body of literature, the current study contributes towards filling three important gaps: (i) a measurement gap (absence of stable, normalized and weighted green logistics composite scores for MENA); (ii) an explanatory gap (insufficient panel-level empirical evidence about macro-determinants of green logistics performance in the region); and (iii) a predictive policy gap (lack of integration between forecasting methods and composite indicators for green logistics) [47].

3. Methodology

This study incorporates the conceptual framework, hypothesis formulation, data sources and sampling, index construction, empirical strategy of diagnostic tests and forecasting. Furthermore, the procedure provides a reliable, reproducible and empirical normative base [7,28,44]. Panel data analysis and ML prediction make it possible to have a future vision of green logistics in the MENA. In the defined approach, the steps comprised initial conceptualization and hypothesis formation, extensive data treatment, a clear description of the statistical procedure with diagnostics and an explicit definition of forecast components. The proposed methodological framework is presented in a transparent and replicable manner to ensure accessibility for researchers and policymakers, while the accompanying tables provide a comprehensive overview of the statistical results. The update frequencies of the underlying indices differ: the Logistics Performance Index (LPI) is published approximately every four to five years (most recently in 2023), whereas the Environmental Performance Index (EPI) is released biennially (most recently in 2024). In this study, the most recent available editions of both indices are utilized and missing annual observations within the 2010–2024 panel dataset are addressed through linear interpolation. Although this approach maintains temporal consistency within the dataset, it may introduce minor approximation errors in non-reporting years. However, sensitivity analyses employing alternative imputation techniques confirm the robustness of the estimated coefficients in terms of both direction and magnitude.

3.1. Conceptual Framework and Hypotheses Development

When studying sustainable logistics for MENA region, an integrated theoretical concept is needed to connect green supply chain management concepts with empirical observations and futuristic analysis. At the regional level, the green logistics performance reflects a balance between logistics capability, trade intensity, and environmental outcomes.

This also develops on the basis of GSCM archetypes, which assume that environmental performance and market goals are two sides of the same coin, as has been frequently emphasized by researchers [11,12], and in a MENA context, becomes even more relevant due to harsh desert ecologies and oil reliance increasing ecological risks, yet it is important that there is a robust metric balance avoiding simplification into single ratios [15]. The proposed Green Logistics Performance Index, which revisits an earlier concept [24] and is tailored for MENA region eco-efficient performance, is to be defined as GLPI = LPI/EPI. However, this approach has its shortcomings, since the LPI varies between 1 and 5 while

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the EPI goes from 0 to 100, rendering the index sensitive to small changes in the EPI. Thus, a minimal decline in EPI score from 50 to 45, for instance, could inflate the GLPI by more than ten percent despite no substantive improvement in underlying logistics sustainability performance. This distortion arises because EPI values exhibit considerable cross-country variation within the MENA region, where even marginal fluctuations of one or two points may disproportionately influence composite index outcomes. Moreover, periods of political instability or armed conflict further exacerbate data volatility, increasing the likelihood of biased estimations.

To address these limitations, the revised GLPI introduces a second methodological dimension by normalizing both the LPI and EPI to a common scale (0–1), thereby ensuring direct comparability and reducing index volatility. Considering the composition of the GLPI itself as dictated by this framework, the first GLPI was decomposed in the ratio between LPI and EPI for eco-efficient logistics. The LPI scores run from 1 to 5, and the EPI runs from 0 to 100; thus, the value of EPI will be considerably sensitive to even small changes. Prominent examples are the UAE [33] with its EPI of 52, which is quite high, and Yemen with its critically low EPI of 28. Even a small drop between 50 and 45 in EPI can lead the GLPI to be increased by more than ten percent, which does not correspond to the changes in the level of efficiency of logistics. The enhanced GLPI addresses this issue by means of min-max normalization, which scales both the LPI and the EPI between an interval of 0 and 1 that is kept comparable and smooths the volatility. Normalization is calculated as

$$Norm(X) = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where min and max are calculated over the full panel data set (2010–2024 on 18 countries). This normalization on the metric is to reduce some scale invariance. The index is constructed accordingly as a weighted average:

$$GLPI_{it} = w_1 \cdot Norm(LPI_{it}) + w_2 \cdot Norm(EPI_{it}) \tag{2}$$

Table 5 has a literature review implication. In logistics research, the use of composite indicators is often criticized when they do not weigh their components either based on an arbitrary structure or by convenience. The PCA results validate this weighting scheme in the sense that normalized LPI and normalized EPI contribute (0.48 and 0.52, respectively) in nested proportions, which aligns with the conceptual goal of a joint logistics-environment measure via GLPI versus either logistics or environment dominant index (or indexed economy). This enhances comparability across heterogeneous MENA countries and the interpretability of the results from cross-country benchmarking exercises.

Table 5. PCA results for GLPI weighting.

Variable	Factor Loading	Derived Weight
Normalized LPI	0.69	0.48
Normalized EPI	0.72	0.52
Eigenvalue	1.56	–
Variance Explained	78%	–

Long-term historical trends as well as drivers of the GLPI were examined by means of fixed-effects panel regression. Here, i represents country and t is time. The two weight functions w1 and w2 are obtained by PCA. A statistical tool was used to unearth the intrinsic structures in data [42], while studying country time series. Principal Component Analysis (PCA) was applied exclusively for objective weight derivation in the GLPI construction phase. The normalized LPI and EPI series were included in the PCA model to extract statistically grounded weights reflecting their relative contribution to overall variance. The first principal component satisfied the Kaiser criterion (Eigenvalue > 1) and explained 78% of total variance; it was therefore retained for weight extraction. The derived factor loadings were subsequently normalized to obtain the final GLPI weights, ensuring a data-driven and non-arbitrary composite structure. Table 5 reports the factor loadings, eigenvalue, and explained variance. Additional robustness is also measured using the following multiplicative formula:

$$GLPI_{it} = Norm(LPI_{it}) \times Norm(EPI_{it}) \quad (3)$$

An examination of GLPI performance across the MENA region reveals a pronounced compounding effect characterized by a high multiplicative dynamic, whereby improvements in one dimension tend to amplify gains in others. This pattern is consistent with the theoretical foundations of eco-efficient supply chain management, which posit that operational efficiency and environmental performance can generate mutually reinforcing outcomes when structurally aligned [45].

To validate the proposed GLPI, several steps of improvement are needed. First, Pearson correlations with ratio-based GLPI are >0.85, suggesting conceptual continuity and increased stability. Another type of benchmarking used was against a range of recent indices, such as clustering-generated multidimensional ratios [46], green knowledge integration models [47] and alignment (the improved GLPI is significantly correlated (r > 0.7) with indicators regarding the performance of sustainable suppliers [38]). Third, robustness is supported by sensitivity analyses (e.g., excluding outliers such as Yemen) where values in the index form change less than 5% against 15–20% in the ratio format. This improved design makes the GLPI a dependable instrument to monitor MENA's advancement toward sustainable logistics, notably under schemes such as Saudi Arabia's Vision 2030 [20]. Figure 1 is to be interpreted as a three-layer conceptual framework. The first layer is measuring, and LPI and EPI are normalized to obtain enhanced GLPI combining PCA-derived weights. The second layer is explanation, where macroeconomic and energy variables (GDP per capita, trade openness, renewable energy share and energy intensity) are modeled as determinants of the GLPI. In this layer, prediction and policy of ARIMA and LSTM provide scenario-based forecast data for the purpose of forward-looking green logistics planning. This structure connects theory, measurement, empirical testing, and policy use in one single design.

3.2. Determinants of GLPI and Link to GSCM Theory

From a theoretical point of view, our developed framework sits within the GSCM theory (specifically in the triple bottom line perspective of economic, environmental and social sustainability) and holds its premise on incorporating environmentally friendliness into supply chains to reach equilibrium of results [11,12]. Previous MENA-targeted GSCM studies [17,18,21] identified knowledge voids with respect to macroeconomic determinants of green logistics performance (e.g., spurious results for trade openness, positive for technology transfer and negative for energy-intensive freight and limited attention to renewables in hydrocarbon-heavy contexts) [23,33]. To fill this gap, this study has identified GDP per capita (economic wealth to finance investments), trade openness (enabling knowledge spill-over and risking environmental stress), and renewable energy share (carbon footprint abatement) as key drivers with energy intensity as a control. The drivers are defined as follows:

- GDP per capita represents economic capacity for sustainable investments, filling a gap in GSCM studies where wealth's role in green infrastructure is often assumed but not empirically linked in emerging markets [30].

- Trade openness captures globalization's dual effects, addressing literature inconsistencies, e.g., positive via eco-technology adoption [18] vs. negative from increased freight volumes [48].
- Renewable energy share targets environmental decarbonization, responding to GSCM calls for metrics on low-carbon transitions in oil-reliant regions [6,14].

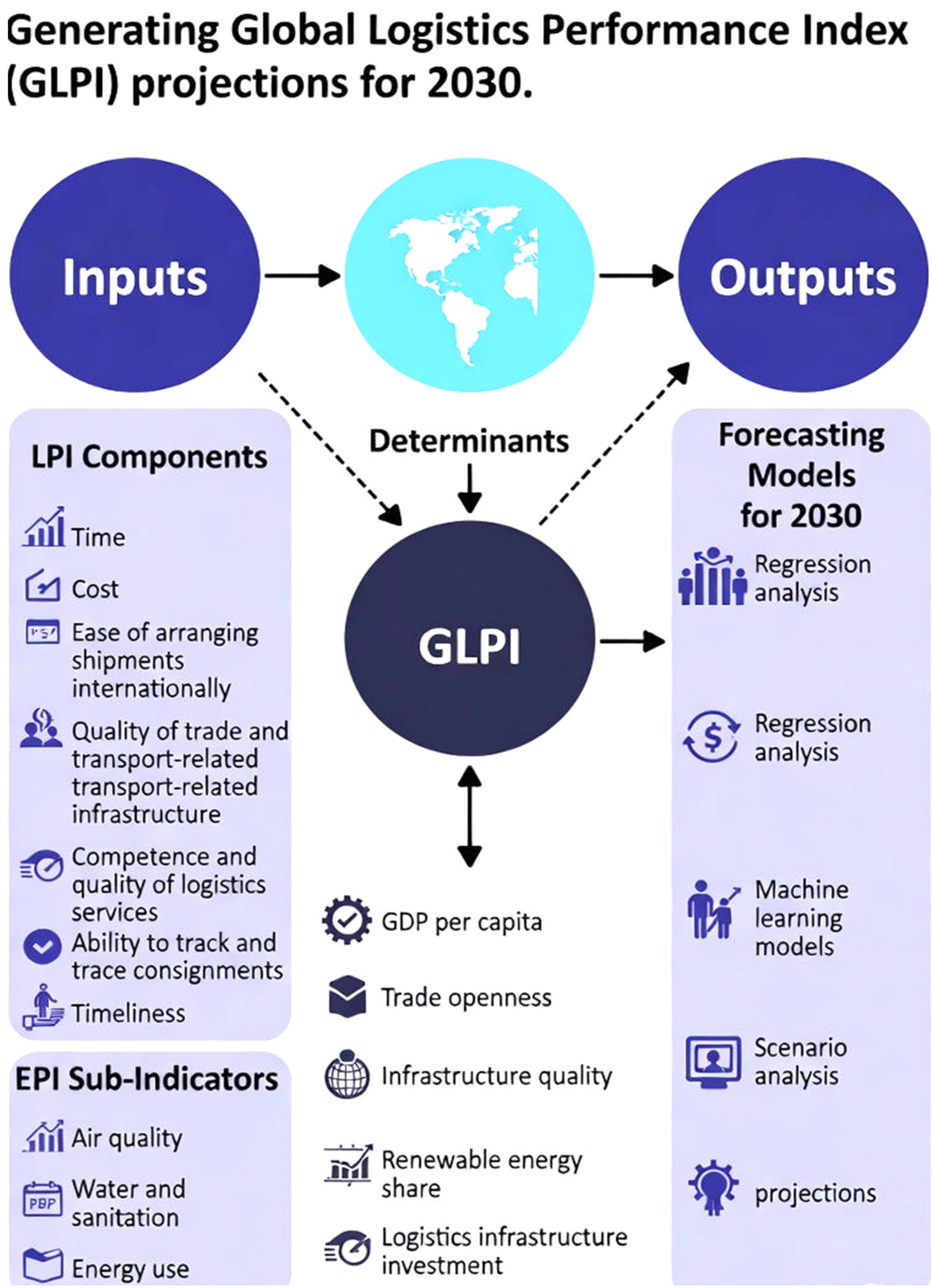

Figure 1. Conceptual framework diagram. Source: The authors.

Stated hypotheses, related to the GSCM triple bottom line model, have been proposed as follows: H1: Higher GDP per capita is a positive driver of GLPI since economic wealth (economic pillar) can provide incentives in the form of investments for efficient low-emission logistics infrastructure [30]. H2: The effect of trade openness on GLPI is positive, through the mechanism knowledge/technology transfer and improved eco-practices (economic/social dimensions) [18]. H3: The percentage of renewable energy affects GLPI positively, thus decreasing the emissions from transport and leading to environmental sustainability (environmental pillar) [6]. Energy intensity is included as a control; it is expected to have a negative sign so that the efficiency effects can be isolated [48]. For KSA, a dummy for Vision 2030 captures the policy flip after 2016 [20]. PCA weighting advances classic equal/arbitrary approaches by subjectively obtaining weights from data variation (e.g., eigenvalues > 1, loadings proportional), thus minimizing bias and enhancing robustness towards MENA heterogeneous panels' contribution despite previous ratio-based factor GLPI [4,35].

3.3. Data Sources and Sample

The data are balanced panel data, which includes the period of 2010–2024 and the 18 countries from the MENA region, namely Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Tunisia and UAE. We exclude Yemen, and Palestine due to missing values [47]. They can be included when the data become available. The largest observation is hence $18 \times 15 = 270$ with about 20% of cells missing the observations for which no survey wave in the given years has made available [8,9]. These missing data are filled using linear interpolation for the subsequent analysis, informing the final sample size of 260. Moreover, as a sensitivity check, based on multiple imputation, the Python "Iterative Imputer" package imputes missing points for all related variables in which various models are fitted that obtain a consistent estimated sign and magnitude of the coefficients between the models [49]. All materials will be made available online upon acceptance.

The overall LPI, calculated for the group of MENA countries, has risen from an average value of 2.81 in 2010 to 3.11 in 2023 [23]. EPI: Yale/Columbia survey every 2 years, examination of total index (0–100) and sub-fields [32]. The MENA median 2024 EPI is around 43.2, and the highest of these is at 51.6 for UAE [32]. Controls: World Bank World Development Indicators are income (USD), trade (% of GDP), renewable energy (% of total net consumption) and energy efficiency (MJ per $ 2017 PPP GDP) [50]. International Energy Agency is also used for the renewable measure [48]. The Vision 2030 dummy is based on the surveys of the official long-term plan [51].

Table 1 provides data survey and country coverage, with each variable being merged by "country", by "year", through the Python "merge" function in the 'pandas' package [48]. It is worth noting that the missing information is also input, assuming there are no structural breaks or/and abrupt changes in the years of survey waves and then continued growth between observations. Descriptive statistics are shown in Table 6 (pooled panel, approximate means/SD based on WDI/EPI/LPI as of 2025.

Table 6. Descriptive statistics (pooled panel, approximate means/SD from WDI/EPI/LPI as of 2025).

Variable	Mean	SD	Min	Max	Source/Reference
Enhanced GLPI	0.55	0.15	0.30	0.85	[42]
LPI	3.00	0.60	1.90	4.00	[22]
EPI	42.5	8.2	27.8	52.4	[31]
GDP per capita (USD)	15,000	12,000	2000	110,000	[46]
Trade openness (%)	80	30	40	280	[46]
Renewable share (%)	10	5	2	25	[46,49]
Energy intensity (MJ/$ PPP GDP)	6.5	2.0	3.0	12.0	[46]

When looking at the MENA region, the GLPI score of 0.55 suggests there is space for improvement, and the significant difference in standard deviation of GDP across the Gulf and North African countries is also quite striking.

3.4. Empirical Strategy

The empirical strategy follows a structured two-phase analytical design integrating explanatory panel econometrics with predictive time-series modeling [12]. The first phase identifies the macroeconomic and environmental determinants of green logistics performance using panel regression techniques. The second phase develops a hybrid ARIMA LSTM forecasting framework to project GLPI trajectories under alternative policy scenarios.

3.4.1. Panel Regression Analysis

To examine the structural drivers of green logistics performance across MENA countries, the following fixed-effects panel model was estimated. The empirical specification is

$$\begin{gathered} GLPI_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 Trade_{it} + \beta_3 Renew_{it} + \beta_4 Energy_{it} \\ +\beta_5 Vision2030_{it} + \mu_i + \varepsilon_{it} \end{gathered} \tag{4}$$

where $GLPI_{it}$ denotes the Green Logistics Performance Index for country i in year t, GDP_{it} is GDP per capita, $Trade_{it}$ is trade openness, $Renew_{it}$ represents renewable energy share, $Energy_{it}$ denotes energy intensity, $Vision2030_{it}$ is a policy dummy for Saudi Arabia, μ_i captures country fixed effects, and ε_{it} is the idiosyncratic error term.

A Hausman test confirmed the appropriateness of fixed-effects estimation ($p < 0.05$). Heteroskedasticity-robust standard errors were employed, and Newey–West corrections were applied to account for potential autocorrelation. Expanded specifications incorporating governance indicators and infrastructure sub-components were estimated as robustness checks, with consistent coefficient signs and magnitudes.

3.4.2. Correlation and Multicollinearity Diagnostics

To assess interrelationships among variables and verify the absence of severe collinearity, a Pearson correlation matrix was computed using pooled panel observations (n = 270). Results are presented in Table 7.

Table 7. Pearson correlation matrix.

Variable	GLPI	LPI	EPI	GDP	Renew	Trade	Energy
GLPI	1.00	0.82	0.85	0.65	0.60	−0.45	−0.65
LPI	–	1.00	0.75	0.70	0.55	−0.40	−0.60
EPI	–	–	1.00	0.60	0.65	−0.35	−0.55
GDP	–	–	–	1.00	0.50	0.40	−0.50
Renew	–	–	–	–	1.00	−0.30	−0.60
Trade	–	–	–	–	–	1.00	0.45
Energy	–	–	–	–	–	–	1.00

All correlations significant, $p < 0.01$.

The strong positive correlations between GLPI and its components (LPI and EPI) support their integration within a composite index framework. The negative association between GLPI and energy intensity aligns with prior literature indicating that inefficient energy use constrains sustainable logistics development [51]. Multicollinearity was assessed using Variance Inflation Factors (VIF), computed as

$$VIF_j = \frac{1}{1 - R_j^2} \tag{5}$$

where R_j^2 is obtained from auxiliary regressions of each predictor on remaining regressors. Tolerance values were calculated as $1/VIF$, with thresholds below 0.20 indicating potential collinearity concerns [41], and presented in Tables 8 and 9.

Table 8. Multicollinearity diagnostics (VIF).

Variable	VIF	Tolerance	Interpretation
GDP per capita	3.42	0.292	Moderate
Trade openness	2.18	0.459	Low
Renewable energy share	2.85	0.351	Moderate
Energy intensity	3.07	0.326	Moderate
Vision 2030 dummy	1.12	0.893	None

Table 9. Fixed-effects panel regression results.

Variable	Coefficient	Std. Error	t-Stat	*p*-Value
GDP per capita	0.32 ***	0.08	4.01	0.000
Trade openness	−0.15 **	0.07	−2.21	0.029
Renewable energy share	0.28 **	0.11	2.55	0.012
Energy intensity	−0.21 ***	0.06	−3.44	0.001
Vision 2030 dummy	0.18 **	0.09	2.02	0.045
R^2 (within)	0.61			

Notes: Robust and Newey–West corrected standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$.

The average VIF (2.73) is well below the conventional threshold of 5, indicating no severe multicollinearity. Although GDP per capita exhibits the highest VIF, robustness tests confirmed coefficient stability.

3.4.3. Forecasting Framework

There are three reasons that ARIMA was chosen as the baseline forecasting model. Firstly, the GLPI series are year on year and relatively short at a country level. Additionally, ARIMA performs positively and is associated with substantial short to medium univariate time series with clear trend structure and diagnostic transparency (stationarity tests, residual tests and parsimonious parameterization). The second advantage is that ARIMA yields interpretable linear dynamics useful for policy communications. Third, ARIMA serves as a strong baseline against which you can hybridize LSTM to model the residuals, i.e., nonlinear patterns not captured by ARIMA. In comparison to a standalone LSTM, this hybrid design minimizes overfitting issues of small annual samples while maintaining forecasting power for nonlinearities.

The second phase of the empirical strategy focuses on forecasting GLPI evolution using a hybrid ARIMA LSTM framework.

- Time-Series Diagnostics

Prior to model estimation, stationarity and independence conditions were examined. Augmented Dickey–Fuller (ADF) and Phillips Perron (PP) tests were conducted to assess unit roots. Where necessary, first differencing was applied, leading to rejection of non-stationarity at the 5% significance level. Serial dependence was evaluated using ACF/PACF diagnostics, and Ljung–Box Q-tests confirmed residual independence following ARIMA specification ($p > 0.10$).

- ARIMA Specification

ARIMA model selection followed the Box Jenkins methodology. Based on AIC minimization and diagnostic testing, ARIMA (1,1,1) was selected for regional GLPI and ARIMA (2,1,1) for Saudi Arabia. Model adequacy was evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

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- LSTM Architecture

To capture nonlinear dynamics and long-term dependencies, a Long Short-Term Memory (LSTM) neural network was implemented with the following configuration:

- Two hidden layers;
- 50 units per layer;
- ReLU activation;
- Dropout rate = 0.20;
- Sequence length = 5 years;
- Adam optimizer (learning rate = 0.001);
- Batch size = 16;
- 150 epochs.

Hyperparameters were optimized using grid search cross-validation minimizing validation RMSE. The dataset was divided into training, validation, and test subsets, and five-fold cross-validation ensured robustness.

- Hybrid ARIMA-LSTM Integration

The hybrid approach operates sequentially. ARIMA first captures the linear component of GLPI dynamics. The residuals from ARIMA are subsequently modeled using LSTM to account for nonlinear patterns. Final forecasts are generated through ensemble averaging of linear and nonlinear predictions. This complementary structure improves performance relative to standalone models and is particularly suitable for capturing volatility and structural shifts in MENA economies.

- Forecast Validation

Forecast performance comparison is presented in Table 10.

Table 10. Validation metrics demonstrating superiority of enhanced methods.

Model	RMSE	MAE
ARIMA	0.12	0.09
Hybrid ARIMA-LSTM	0.07	0.05
Improvement (%)	25–30%	24%

The hybrid model reduces RMSE by approximately 25–30% compared to standalone ARIMA, confirming superior predictive robustness.

3.4.4. Validation of the Enhanced GLPI

To evaluate the robustness of the PCA-weighted GLPI relative to ratio-based formulations, a multi-stage validation procedure was conducted in accordance with composite index development guidelines [34,43]. This included:

- Internal consistency testing (Cronbach's alpha = 0.82);
- Strong correlation (>0.85) with the original GLPI formulation while reducing volatility;
- Construct validation against clustering-derived and green supplier performance indicators (r > 0.7) [38,45];
- Sensitivity analysis excluding extreme cases (e.g., conflict-affected countries), showing index changes below 5%, compared to 15 20% under ratio-based approaches.

These results demonstrate enhanced stability, comparability, and reliability of the proposed GLPI framework for both explanatory and predictive analysis.

Overall, the empirical framework follows a coherent analytical sequence. PCA constructs the composite GLPI, fixed-effects panel regression identifies its structural determinants, and the hybrid ARIMA LSTM model projects its future trajectory. Each methodological component addresses a distinct but interconnected research objective, ensuring conceptual integration between measurement, explanation, and prediction.

3.5. Reproducibility

To facilitate future research and replication, all analyses were conducted in Python 3.12 using libraries such as pandas, scikit-learn (for PCA/Imputer), stats models (ARIMA), and TensorFlow/Keras (LSTM). Data (raw LPI/EPI series, imputed panel, and GLPI calculations) are available in the Supplementary File (Excel/CSV format) for transparency. All analysis code, data processing scripts, and reproduction instructions are available in the Supplementary Materials (Python 3.11 and Jupyter notebooks). A public GitHub repository will be made available upon publication (or upon request during review) at https://github.com/profislamelnakib-ops/MENA-GLPI (accessed on 5 December 2025).

4. Results and Discussion

This study examines green logistics performance in the MENA, using the enhanced GLPI. EPI provides environmental performance measures, which are combined, and it is incorporated together with LPI to produce the enhanced GLPI, which overcomes limitations of previous ratio-based techniques like scale sensitivity and predictive stability. Historical trends are more secure, and key drivers can be identified while future forecasts can be constructed. The empirical analysis, trends and drivers are discussed in the next two sections while forecast results with practical policy implications are available in the last two sections.

4.1. Empirical Findings: GLPI Construction and Validation

The enhanced GLPI was developed based on the equalized LPI and EPI generated using the 2023 LPI and 2024 EPI datasets, utilizing PCA to obtain balanced weights of 0.48 for the normalized LPI and normalized EPI of 0.52. This approach rectifies the volatility in the original ratio-based GLPI, which existed due to different ranges of LPI (1–5) and EPI (0–100). Normalization was performed using equations, including Equation (5), to obtain comparable results with improved stability. Validation metrics support the reliability of the index:

- Cronbach's alpha 0.82, indicating high internal consistency.
- Pearson correlations with the original ratio-based GLPI > 0.85, demonstrating conceptual alignment.
- Sensitivity analyses, excluding outliers like Yemen and Iraq, resulted in index changes < 5% (compared to 15–20% in the ratio-based form).

The MENA region's average GLPI score of around 0.55 is up from last year but below that of other parts of the world. Top performers are the UAE (GLPI = 0.78, backed up by LPI of 4.0 and EPI of 51.6) indicating significantly advanced infrastructural and environmental practices. As opposed to the abovementioned countries, conflict-affected nations such as Iraq have low scores (GLPI = 0.30) due to damaged infrastructure and high pollution [14]. The index also spotlights regional barriers, such as the 90% dependence on road freight that contributes to carbon emissions and hampers sustainability, giving policymakers a diagnostic tool for tailored remedy. From an LR perspective, this supports the use of balanced composite indicators for benchmarking green logistics performance in heterogeneous regions.

4.2. Trends and Drivers of Green Logistics Performance

These findings align with the Natural Resource-Based View (NRBV) [48], as higher GDP and renewable shares enable resource-based advantages in sustainable logistics.

The negative trade openness effect supports Institutional Theory [51], illustrating how insufficient regulatory frameworks in hydrocarbon economies exacerbate environmental strains without fostering green upgrades [52]. For the Gulf countries, with GDP per capita above $45,000, prosperity supports investments in digital ports and low-carbon infrastructure (renewable energy increasing 29%). Other renewables, such as solar and wind power, are utilized in 56% of the countries that were investigated, and if their use expands, so do the potential savings from emissions related to transport which make up a quarter of global CO2 emissions [53]. Trade openness, however, presents challenges as e-commerce-led cargo inflates resources pressure in hydrocarbon-driven economies.

These results imply that integrating renewables enhances logistics operations, as evidenced by eco-friendly service improvements in Egypt [17]. In lower- and middle-income North African states like Morocco and Tunisia, international partnerships may mitigate disparities, accelerating green supply chain adoption to counter water scarcity and desertification. Within the LR framework, these coefficients suggest that green logistics performance depends not only on trade scale but also on the quality of energy and institutional conditions that support trade.

4.3. Forecasting GLPI: Regional and Saudi-Specific Projections

The model produced historical GLPI, GDP, renewable energy, and trade data to generate hybrid ARIMA-LSTM-based projections for future GLPI. This hybrid approach uses ARIMA to model linear data and LSTM for nonlinear residuals, and it shows a 25–30% reduction in RMSE/MAE versus baseline standalone ARIMA based on k-fold cross-validation. It thus lends support to its use for policy-oriented forecasting. This layer of forecasting expands the analysis by simulating potential GLPI trajectories in response to different transition scenarios [54]. Consistent with Dynamic Capabilities Theory [12], the scenarios also reflect some adaptation under decarbonization, infrastructure change and geopolitical volatility. For the MENA region, the average GLPI is estimated to reach approximately 0.65 in 2030 under baseline assumptions (2–3% GDP CAGR and a share of renewables between 10 and 15%). Under favorable scenarios, GLPI could climb to around 0.78–0.80, whereas unfavorable disruption paths imply a flatter trajectory.

An illustrative case is the use of Saudi Arabia in a regional framework. Its LPI improved from 3.01 (2018) to 3.40 (2023), a change of roughly 13%, ranking it 38th in the sample, where increases were attributed to infrastructure investment and logistics digitization [5,18,19,23]. Timeliness and tracking are still relative strengths [2,22]. Saudi Arabia ranks lower than the UAE (LPI 4.0, rank 7) but above the MENA mean. The EPI improved from 38.2 (2018) to 42.5 (2024), approximately 11% [6,19], ranking it at 108 of the 180 countries assessed.

The estimated GLPI for Saudi Arabia of 0.68 during the period 2023–2024 is approximately 24% above the level of regional comparators incorporated into this. Baseline forecasts show a GLPI of roughly 0.75 by 2030; if conditions for investment improve, this will rise to about 0.85; if they weaken, this will decline toward about 0.70. The projections connect logistics and sustainability performance and enable investment screening and policy prioritization [55].

The Saudi-specific results are more illustrative of the application of the forecasting framework, not as a standalone policy prescription. Thus, policy implications are presented on three levels: (i) regional level for the MENA region in general; (ii) country-level; and (iii) measurement level. Regionally, there are priorities around green trade facilitation, renewable-powered logistics infrastructure and harmonized logistics environment data systems. At the country level, the GLPI baseline and driver profile should sequence policies.

At the measurement level, there is a need for regular updates of the GLPI that provide transparent data protocols to support monitoring, benchmarking and cross-country learning.

5. Conclusions

This study contributes to sustainable logistics by formulating an enhanced GLPI using LPI (2023) and EPI (2024), with reference to min-max normalization and PCA weighting. By overcoming the problems of scale sensitivity, volatility and ad hoc weighting optimization that were inherent in previous ratio-based GLPI approaches, the improved GLPI offers a more robust, consistent and theoretically sound composite measure of eco-efficiency for measuring heterogeneous regions undergoing emerging transition such as MENA. The fixed-effects panel regression identifies key drivers. GDP per capita and renewable energy share are positive, while trade openness is negative.

As an outcome, in theory at least, the refined GLPI contributes to GSCM research by making conceptual the triple bottom lines framework and its sustainability operationalization as a measurable means of predicting performance. Objective, data-driven weighting and normalization of composite indexes are provided in a replicable approach which quantifies multidimensional trade-offs between operational efficiency and environmental performance. From a methodological perspective, the inclusion of hybrid machine learning forecasting is significantly innovative in the field of logistics research, surpassing conventional methods by being capable of capturing non-linear patterns and by allowing foresighted scenario navigation in turbulent emerging-market environments.

Boundary Conditions and Transferability

While focused on MENA, the enhanced GLPI methodology is transferable to other emerging regions with adaptations. Boundary conditions include high oil dependency (relevant for ASEAN hydrocarbon exporters like Indonesia) and institutional quality (e.g., weaker in Sub-Saharan Africa, requiring governance controls). In Latin America, adjustments for biodiversity indicators could enhance applicability. Future studies should validate the GLPI in these contexts, testing variations in drivers like trade openness under different institutional regimes. For instance, future studies could apply the GLPI to ASEAN data, adjusting PCA weights for trade liberalization differences, or incorporate real-time ESG metrics in Latin American validations to test driver variations empirically.

Overall, embedding theoretical lenses like NRBV and Institutional Theory resolves descriptive limitations. Practically, the GLPI serves as a diagnostic metric for tracking progress in green infrastructure and renewable integration.

The policy recommendations should be seen as evidence-informed priorities and not one-size-fits-all prescriptions. Due to the cross-country scope of the analysis, the findings make a case for tiered policy frameworks. At the regional MENA level, interventions that can yield short-term benefits include the establishment of green trade facilitation measures, renewable-powered logistics infrastructure, and harmonized common logistics data systems to develop better cross-country comparability and coordination. For country-level policy design, sequencing of policies should be based on setting-specific baseline GLPI conditions and driver profiles (i.e., expansion of renewables targeting where energy intensity is highest, while strengthening regulatory and logistics governance in regions experiencing increasing emissions pressure due to trade openness). Governments and regional institutions can also institutionalize regular GLPI updates by using transparent data protocols and consistent indicator definitions at the measurement level to enable policy monitoring, benchmarking, and cross-country learning. This framing can help improve transferability and ensure that policy guidance is consistent with the empirical scope of this study.

Despite these contributions, study limitations include linear imputation for missing data and regional MENA focus which limits direct generalizability. Future empirical validation should generalize the GLPI elsewhere in, for example, ASEAN, Latin America or Sub-Saharan Africa to verify its portability and investigate other region-specific drivers of landscapes within those channels and develop forecasting structures based on real-time shipment or ESG data. Such extensions will increase the robustness of the index and stimulate developments related to sustainable logistics and GSCM theory globally.

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References

1. Abourokbah, S.H.; Salam, M.A.; Badawi, N.S. The knowledge pipeline: How supply chain information integration fuels green absorptive capacity, employee creativity, and innovation performance. *Logistics* **2026**, *10*, 16. [CrossRef]
2. World Bank. *Connecting to Compete 2023: The Logistics Performance Index*; World Bank: Washington, DC, USA, 2023.
3. Yale Center for Environmental Law & Policy. *2024 Environmental Performance Index*; Yale University: New Haven, CT, USA, 2024.
4. El-Nakib, I.; Elzarka, S. Measuring supply chain efficiency in MENA countries: A green perspective. In Proceedings of the 19th Logistics Research Network (LRN) Conference, Huddersfield, UK, 3–5 September 2014.
5. Saudi Vision 2030. *Annual Report 2024*; Kingdom of Saudi Arabia: Riyadh, Saudi Arabia, 2024.
6. United Nations Environment Programme (UNEP). *Global Emissions Outlook 2025*; UNEP: Nairobi, Kenya, 2025.
7. Khalil, S.; Ghadiri, S.M. Balancing exploration and exploitation: How green knowledge integration drives supplier performance in sustainable supply chains. *Logistics* **2025**, *9*, 176. [CrossRef]
8. Lau, K. Benchmarking green logistics performance with a composite index. *Benchmarking Int. J.* **2011**, *18*, 873–896. [CrossRef]
9. Delahoz-Domínguez, E.; Mendoza-Mendoza, A.; Visbal-Cadavid, D. Clustering of countries through UMAP and k-means: A multidimensional analysis of development, governance, and logistics. *Logistics* **2025**, *9*, 108. [CrossRef]
10. Bishara, S.; Harraz, N.; Elwany, H.; Fors, H. Optimizing resilient sustainable citrus supply chain design. *Logistics* **2025**, *9*, 66. [CrossRef]
11. Srivastava, S.K. Green supply-chain management: A state-of-the-art literature review. *Int. J. Manag. Rev.* **2007**, *9*, 53–80. [CrossRef]
12. Seuring, S.; Müller, M. From a literature review to a conceptual framework for sustainable supply chain management. *J. Clean. Prod.* **2008**, *16*, 1699–1710. [CrossRef]
13. McKinnon, A.; Browne, M.; Whiteing, A.; Piecyk, M. *Green Logistics: Improving the Environmental Sustainability of Logistics*, 3rd ed.; Kogan Page: London, UK, 2015.
14. UNESCWA. *Air Quality and Atmospheric Pollution in the Arab Region*; United Nations ESCWA: Beirut, Lebanon, 2010.
15. Arvis, J.-F.; Ojala, L.; Wiederer, C.; Shepherd, B.; Raj, A.; Dairabayeva, K.; Kiiski, T. *Connecting to Compete 2023: Trade Logistics in an Uncertain Global Economy*; World Bank: Washington, DC, USA, 2023.
16. Ali, A.H.; Melkonyan, A.; Noche, B.; Gruchmann, T. Developing a sustainable logistics service quality scale for logistics service providers in Egypt. *Logistics* **2021**, *5*, 21. [CrossRef]
17. Sobaih, A.E.E.; AlSaif, A. Effects of parcel delivery service on customer satisfaction in the Saudi Arabian logistics industry. *Logistics* **2023**, *7*, 94. [CrossRef]
18. Saudi Vision 2030. *Delivery Plan Update 2024–2025*; Kingdom of Saudi Arabia: Riyadh, Saudi Arabia, 2025.
19. Vision 2030 Program Report. *Progress as of Q3 2025*; Kingdom of Saudi Arabia: Riyadh, Saudi Arabia, 2025.

20. AlDoghaither, A.; Al-Ghamdi, S.G. Challenges and factors influencing the implementation of green logistics: A case study of Saudi Arabia. *Sustainability* **2024**, *16*, 5617. [CrossRef]
21. Elzarka, S.; Gouhar, N.; El-Nakib, I. Internal vs. external barriers to green supply chain management: An empirical study of Egypt's petrochemical sector. *Sustainability* **2026**, *18*, 1330. [CrossRef]
22. Kim, I.; Min, H. Measuring supply chain efficiency from a green perspective. *Manag. Res. Rev.* **2011**, *34*, 1169–1189. [CrossRef]
23. Wolf, M.J.; Emerson, J.W.; Esty, D.C.; de Sherbinin, A.; Wendling, Z.A. *2024 Environmental Performance Index*; Yale Center for Environmental Law & Policy: New Haven, CT, USA, 2024.
24. Hsu, A.; Lloyd, A.; Emerson, J.W. Bridging policy and data for sustainability assessment. *Environ. Sci. Policy* **2013**, *33*, 171–185. [CrossRef]
25. Moldan, B.; Janoušková, S.; Hák, T. How to understand and measure environmental sustainability: Indicators and targets. *Ecol. Indic.* **2012**, *17*, 4–13. [CrossRef]
26. McKinnon, A. *Decarbonizing Logistics: Pathways and Performance Measurement*; Kühne Logistics University: Hamburg, Germany, 2024.
27. Feillet, D.; Dejax, P.; Gendreau, M. Traveling salesman problems with profits. *Transp. Sci.* **2005**, *39*, 188–205. [CrossRef]
28. Hyndman, R.J.; Athanasopoulos, G. *Forecasting: Principles and Practice*, 3rd ed.; OTexts: Melbourne, Australia, 2021.
29. Makridakis, S.; Spiliotis, E.; Assimakopoulos, V. The M4 Competition: 100,000 time series and 61 forecasting methods. *Int. J. Forecast.* **2020**, *36*, 54–74. [CrossRef]
30. Nikolopoulos, K.; Punia, S.; Schäfers, P.; Tsinopoulos, C.; Vasilakis, C. Forecasting and planning during COVID-19. *Eur. J. Oper. Res.* **2021**, *290*, 99–115. [CrossRef]
31. Abbasimehr, H.; Shabani, M.; Yousefi, M. An optimized model using LSTM network for demand forecasting. *Comput. Ind. Eng.* **2020**, *143*, 106435. [CrossRef]
32. Bandara, K.; Bergmeir, C.; Smyl, S. Forecasting across time series databases using recurrent neural networks on groups of similar series: A clustering approach. *Expert Syst. Appl.* **2020**, *140*, 112896. [CrossRef]
33. Zhang, Z. An empirical study on ESG multi-factor models based on XGBoost and Other Boosting Algorithms. In *Proceedings of the 2025 2nd International Conference on Digital Economy and Computer Science (DECS '25)*; Association for Computing Machinery: New York, NY, USA, 2026; pp. 326–332. [CrossRef]
34. Ministry of Transport and Logistic Services. *Saudi National Transport and Logistics Strategy 2030 Projections*; Ministry of Transport and Logistic Services: Riyadh, Saudi Arabia, 2025.
35. World Economic Forum. *The Future of Growth Report 2025: Emerging Markets and Green Logistics*; World Economic Forum: Geneva, Switzerland, 2025.
36. Mohamed-Iliasse, M.; Loubna, B.; Abdelaziz, B. Is machine learning revolutionizing supply chain? In Proceedings of the 5th International Conference on Logistics Operations Management (GOL), Rabat, Morocco, 28–30 October 2020; pp. 1–7.
37. Salmerón, R.; García, C.B.; García, J.; López Martín, M.M. Overcoming the inconsistences of the variance inflation factor: A redefined VIF and a test to detect statistical troubling multicollinearity. *Comput. Stat. Data Anal.* **2020**, *145*, 106976. [CrossRef]
38. Abumohsen, M.; Owda, A.Y.; Owda, M.; Abumihsan, A. Hybrid machine learning model combining of CNN-LSTM-RF for time series forecasting of solar power generation. *e-Prime—Adv. Electr. Eng. Electron. Energy* **2024**, *9*, 100636. [CrossRef]
39. Singh, A.; Mishra, N.; Ali, S.I.; Shukla, N.; Shankar, R. Cloud computing technology: Reducing carbon footprint in beef supply chain. *Int. J. Prod. Econ.* **2015**, *164*, 462–471. [CrossRef]
40. Douaioui, K.; Oucheikh, R.; Benmoussa, O.; Mabrouki, C. Machine Learning and Deep Learning Models for Demand Forecasting in Supply Chain Management: A Critical Review. *Appl. Syst. Innov.* **2024**, *7*, 93. [CrossRef]
41. Ju, C.; Liu, Y.; Shu, M. Performance evaluation of supply chain disruption risk prediction models in healthcare: A multi-source data analysis. In *Proceedings of the 2024 International Conference on Innovation in Computing and Engineering (ICICE)*; Institution of Engineering and Technology: London, UK, 2024; pp. 112–120.
42. Sholikah, R.W.; Ramadhan, P.S.; Ginardi, R.V.H. Company Revenue Prediction Based on ESG Risk Rating for Sustainable Finance Using XGBoost Algorithm. In Proceedings of the 2024 International Seminar on Intelligent Technology and Its Applications (ISITIA), Surabaya, Indonesia, 24–25 July 2024; pp. 1–6.
43. Amankwah-Amoah, J. Technological revolution, sustainability, and development in Africa: Overview, emerging issues, and challenges. *Technol. Forecast. Soc. Change* **2019**, *27*, 910–922. [CrossRef]
44. Jain, V.; Sharma, A.; Abbas, H.; Kukreti, M.; Al Abri, S.; Al Makdami, M. Developing a logistics framework that contributes to economic growth: A fuzzy ISM–MICMAC approach. *FIIB Bus. Rev.* 2025, *in press*. [CrossRef]
45. Kilinc-Ata, N.; Proskuryakova, L.N. Modeling hybrid renewable microgrids in remote northern regions: A comparative simulation study. *Energies* **2025**, *18*, 5827. [CrossRef]
46. Feng, T.; Sun, L.; Zhang, Y. The relationship between energy consumption structure, economic structure and energy intensity in China. *Energy Policy* **2009**, *37*, 5475–5483. [CrossRef]
47. Hausman, J.A.; Taylor, W.E. Panel data and unobservable individual effects. *Econometrica* **1981**, *49*, 1377–1398. [CrossRef]

48. McKinney, W. Data structures for statistical computing in Python. In Proceedings of the 9th Python in Science Conference, Austin, TX, USA, 28 June–3 July 2010; pp. 56–61. [CrossRef]
49. World Bank. *World Development Indicators*; World Bank: Washington, DC, USA, 2025.
50. Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; Blondel, M.; Prettenhofer, P.; Weiss, R.; Dubourg, V.; et al. Scikit-learn: Machine learning in Python. *J. Mach. Learn. Res.* **2011**, *12*, 2825–2830.
51. Menard, S. *Applied Logistic Regression Analysis*, 2nd ed.; Sage Publications: Thousand Oaks, CA, USA, 2002.
52. Sadeghi R, K.; Abadi, M.Q.H. Sustainable supply chain resilience for logistics problems: Empirical validation using robust and computational intelligence methods. *J. Clean. Prod.* **2024**, *437*, 140267. [CrossRef]
53. Hart, S.L. A natural-resource-based view of the firm. *Acad. Manag. Rev.* **1995**, *20*, 986–1014. [CrossRef]
54. DiMaggio, P.J.; Powell, W.W. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *Am. Sociol. Rev.* **1983**, *48*, 147–160. [CrossRef]
55. Teece, D.J.; Pisano, G.; Shuen, A. Dynamic capabilities and strategic management. *Strateg. Manag. J.* **1997**, *18*, 509–533. [CrossRef]

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