

Article

A Computational Decision Matrix for Sustainable Tourism: Machine Learning Archetypes and Digital Leapfrogging

Thomas Krabokoukis 

Department of Planning and Regional Development, University of Thessaly, Pedion Areos, 38334 Volos, Greece; tkrabokoukis@uth.gr

Abstract

The post-COVID-19 tourism recovery exposes a structural divergence between economic resilience and environmental sustainability. Traditional tourism planning metrics consistently fail to diagnose how macroeconomic growth dynamics decouple from environmental pressures, leaving policymakers without empirical tools to identify structural vulnerabilities or prevent carbon-intensive recoupling during post-crisis transitions. This study integrates macroeconomic, environmental, and digital data across a global panel to map actionable pathways for sustainable tourism transitions. Employing a multi-stage methodology, the analysis first utilizes K-Means clustering ($n = 80$) to isolate the structural fixed effects of baseline destination archetypes driving a K-shaped recovery. Second, using a synchronized environmental panel ($n = 41$), a Decoupling Index evaluates eco-efficiency elasticity to test the alignment between tourism value recovery and aviation-induced CO₂ emissions. Third, regression analysis of an elite digital cohort ($n = 18$) measures dynamic exogenous catalysts, revealing that digital attractiveness, proxied by the global digital nomad market share, is a significantly stronger accelerator of recovery ($\beta = 55.59$, $p = 0.019$) than traditional physical air connectivity ($\beta = -46.48$, $p = 0.036$). Synthesizing these insights, a 2×2 Strategic Decision Matrix ($n = 41$) classifies destinations into Sustainable Leaders, Mass-Market Traps, Value Pivoters, and Vulnerable Laggards. The empirical results demonstrate that pre-pandemic structures do not deterministically dictate recovery ($p > 0.05$, Partial $\eta^2 \leq 0.077$), yet rapid financial recovery often masks deep atmospheric vulnerabilities, with specific absolute decoupling leaders achieving exceptional value expansion alongside strict carbon contraction (e.g., Saudi Arabia, $DE = -0.35$; El Salvador, $DE = -0.26$). This framework provides a data-driven roadmap for policymakers to utilize “soft” digital infrastructure to transition from carbon-intensive, volume-dependent models toward value-optimized, low-emission ecosystems.

Keywords: resilience; machine learning; K-Means clustering; environmental decoupling; digital nomads; destination archetypes; aviation carbon footprint; strategic decision matrix



Academic Editors: Fátima Matos Silva and Isabel Borges

Received: 2 June 2026

Revised: 29 June 2026

Accepted: 1 July 2026

Published: 3 July 2026

Copyright: © 2026 by the author.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

1.1. Research Background and Existing Problems

Tourism activity has been regarded as one primary engine of economic development, particularly for emerging economies seeking to leverage their natural and cultural assets to generate foreign exchange and create jobs [1]. Although tourism expansion is traditionally assumed to correlate linearly with macroeconomic prosperity, recurring disruptions systematically challenge this baseline. Frequent global shocks, ranging from

COVID-19 [2–4] and energy crises [5] to geopolitical conflicts [6] and localized country-level crises [7], demonstrate that excessive tourism reliance can create a structural “trap”. This systemic vulnerability is clearly documented across contemporary indices for highly specialized destinations [8]. This trap typically manifests as a variant of the “Dutch Disease”, where the sector’s overwhelming contribution to the national GDP crowds out other productive industries and exponentially increases exposure to exogenous shocks [9,10]. Consequently, the core problem facing contemporary tourism planning is that blind volume expansion creates severe, non-linear macroeconomic risks that erode absolute regional resilience while systematically masking underlying environmental degradation.

1.2. Existing Research Methods and Limitations

While international arrivals have largely returned to, or even exceeded, pre-pandemic levels [11], the recovery has been profoundly uneven and K-shaped. Some destinations have successfully pivoted toward high-value, premium models that prioritize yield and quality over volume, whereas many others remain locked into mass-market strategies that generate diminishing returns and heightened vulnerability [12,13]. This pronounced asymmetry reveals the limitations of traditional macroeconomic analyses and calls for a more nuanced understanding of destination trajectories. Traditional evaluative methods depend heavily on aggregated, static gross indicators, such as total arrival counts or raw receipt volumes, which fail to capture the multi-tiered trade-offs of post-crisis transitions. Crucially, existing monitoring frameworks exhibit an analytical blind spot: they are incapable of systematically linking carbon decoupling metrics with soft digital infrastructure performance on a global scale.

1.3. The Proposed Methods, Advantages, and Innovations

The present study extends the existing literature by actively addressing this gap. Specifically, it employs a longitudinal machine learning approach (K-Means clustering) on a harmonized panel of 80 countries across pre-pandemic (2015–2019) and recovery (2022–2024) periods to identify structural archetypes based on economic dependence, human capital capacity, and yield [14,15]. Ultimately, this study aims to empirically demonstrate whether destination resilience is merely a passive outcome of global trends or a strategic structural choice, such as the active decoupling of tourist volume from economic value.

Escaping the tourist trap requires a transition to smart destination management. For this purpose, Sustainable Tourism Observatories and global networks such as UN Tourism’s INSTO have been developed [16,17]. By integrating longitudinal datasets and Big Data analytics, this research maps the new reality of post-pandemic resilience [18]. Crucially, this paper represents a paradigm shift in tourism economics by proposing a comprehensive, multi-dimensional evaluation framework at the national level. In doing so, this study actively bridges the theoretical and empirical divide between economic geography, digitalization, and ecological economics within tourism research. It deliberately moves beyond traditional financial metrics by quantifying environmental accountability through tourism-adjusted CO₂ emissions from international aviation. This sector is strategically prioritized because aviation constitutes the most carbon-intensive segment of the global tourism value chain, typically accounting for over 50% of direct tourism-related CO₂ emissions.

By placing this at the forefront of the analysis, the environmental proxy directly captures a primary driver of the sector’s absolute carbon footprint, ensuring that the decoupling assessment reflects the true ecological cost of cross-border mobility. Concurrently, the framework combines supply-side infrastructure (PageRank aviation connectivity) with demand-side economics, while integrating destination digital attractiveness (proxied by the global market share of digital nomads) as a transformative predictor of recovery velocity. In

this context, digital nomads are utilized as a proxy for a destination's "soft" infrastructure (defined herein as the nexus of digital connectivity, remote-work amenities, and modern lifestyle branding) and lifestyle appeal, reflecting the modern shift toward remote-work readiness. Ultimately, it aims to operationalize these insights into an actionable policy simulation framework (a 2×2 decision quadrant) for sustainable transitions.

1.4. Structure, Content, and Main Contributions of This Paper

This paper delivers three interconnected contributions to the existing literature. Methodologically, it introduces a longitudinal, machine learning-driven typology that moves beyond localized tourism studies to establish global structural destination archetypes across disparate macroeconomic regimes. Building upon this typology, the study achieves a novel empirical integration that bridges economic geography with ecological economics by directly embedding environmental accountability into macroeconomic performance and quantifying aviation-induced CO₂ emissions through a scale-invariant decoupling elasticity framework. Finally, from a strategic point, it tests a "soft" digital infrastructure, proxied by global digital nomad market shares, as a dynamic recovery accelerator, translating these multidimensional insights into an actionable 2×2 policy matrix designed for value-optimized tourism transitions.

In this context, the study is structured around four central research questions:

- RQ1: What are the distinct structural archetypes of global tourism destinations based on their economic dependence, human capital quality, and value added (yield), and how does their resilience differ during the transition from the pre-pandemic stability period (2015–2019) to the post-COVID recovery phase (2022–2024)? To address this question, the study utilizes a comprehensive baseline panel of $n = 80$ global economies, enforcing a strict inclusion criterion of complete, non-null longitudinal macroeconomic reporting across both the pre-crisis baseline (T0: 2015–2019) and recovery (T1: 2022–2024) periods.
- RQ2: How does structural archetype affiliation affect the environmental efficiency of a destination, and what is the relationship between economic recovery and the carbon footprint (CO₂ emissions) generated by international air transport? This query evaluates a synchronized sub-sample of $n = 41$ destinations extracted from the core panel, restricted strictly to countries with fully verified, non-interpolated international aviation CO₂ emission reporting for the entire evaluation window.
- RQ3: To what extent do infrastructure and digital attractiveness act as recovery accelerators? Specifically, how does physical air connectivity (measured via PageRank algorithms) interact with digital destination appeal (proxied by digital nomad market share) to predict the recovery velocity and resilience of different structural archetypes? This exploratory associative analysis evaluates an elite digital vanguard cohort of $n = 18$ premier destinations, determined by simultaneous data availability for the specialized global digital nomad market share index.
- RQ4: Which tourism development models demonstrate the optimal balance between economic resilience and environmental sustainability, and what actionable, quadrant-based strategic pathways emerge for policymakers navigating the post-COVID era? This final synthesis operationalizes the multi-tier empirical insights by projecting the synchronized sub-sample of $n = 41$ destinations into a unified strategic policy simulation matrix, ensuring a comparative mapping of overlapping environmental and digital recovery vectors.

These research questions provide a structured approach to exploring the evolving role of tourism in post-pandemic economic landscapes, with a particular emphasis on resilience-building strategies and sustainable transitions. The remainder of this paper is organized as

follows: Section 2 details the methodology, encompassing the data sources, the machine learning clustering techniques (K-Means), and the analytical models employed for economic and environmental assessment. Section 3 presents the empirical results and discusses their implications for the distinct structural archetypes. Finally, Section 4 concludes the study by synthesizing the key findings, outlining actionable policy recommendations through the decision matrix, and identifying avenues for future research.

2. Related Work

Recent empirical studies have increasingly documented the asymmetric and spatially uneven nature of post-COVID tourism recovery. Ref. [2] analyzed territorial resilience across Spanish regions, revealing significant spatial disparities in recovery patterns during the summer of 2020 and attributing these differences primarily to pre-existing levels of tourism dependence and economic diversification. Similarly, Ref. [19] employed clustering techniques to examine the differential impact of the pandemic on Spanish autonomous communities, highlighting how tourism-dependent regions experienced more severe and prolonged downturns. In the Greek context, Ref. [20] investigated regional economic resilience in tourism demand using a three-dimensional (3D) resilience index, demonstrating notable spatial asymmetries linked to sectoral specialization and structural economic characteristics. At a broader level, Ref. [21] proposed a resilience-based framework emphasizing government support, technological innovation, and local belongingness as critical pillars for industry revival, while Ref. [22] provided evidence from Malaysia illustrating K-shaped recovery trajectories between different destination types.

These contributions, along with other single-country or conceptual studies (e.g., [23]), substantially advance the academic understanding of destination vulnerability. However, they predominantly adopt localized (single-country or regional) or strictly conceptual approaches. Consequently, there remains a critical dearth of comprehensive, global, data-driven typologies that integrate economic dependence, human capital quality, and value-added (yield) metrics across both the pre- and post-pandemic periods. By extracting these baseline literature coordinates into this dedicated section, the paper systematically exposes a recurring methodological gap: the absolute absence of an international framework capable of transforming unsupervised machine learning classifications into dynamic environmental decoupling diagnostics. To address this critique, this study benchmarks its multi-stage analytical workflow against contemporary interdisciplinary literature along three strict methodological and thematic pillars.

2.1. Macro-Level Destination Taxonomy and Post-Crisis Clustering

In tourism economics, handling extreme cross-country heterogeneity requires robust unsupervised machine learning strategies to reveal latent structural properties. Recent studies have turned to clustering algorithms to sort destinations without imposing restrictive parametric assumptions. For instance, Ref. [24] successfully deployed a K-Means clustering methodology to evaluate the uneven post-pandemic recovery paths of rural mountain communes, demonstrating that structural baseline capacities strongly mediate a destination's adaptive trajectory. Similarly, Ref. [25] utilized unsupervised cluster analysis to group remote-work and workation hubs based on cost profiles, digital infrastructure, and socio-economic safety metrics.

However, these taxonomic models remain geographically and conceptually constrained. The clustering parameters in the existing literature are either restricted to localized, single-country perimeters or focus strictly on descriptive profiling without linking the generated clusters to downstream macroeconomic constraints, such as carbon emissions elasticity or international aviation dependencies. This study overcomes these boundaries

by using clustering strictly as a foundational baseline filter ($n = 80$) before introducing secondary, scale-invariant performance vectors.

2.2. Environmental Sustainability and Scale-Invariant Decoupling Elasticities

The evaluation of green tourism transitions has evolved from absolute emission tracking to the deployment of elasticity frameworks designed to measure the rate of environmental pressure relative to economic growth. Ref. [26] established a major benchmark by combining a “bottom-up” greenhouse gas inventory with the Tapio decoupling model to construct spatial correlation networks of tourism decarbonization across provincial regimes. This decoupling lens was dynamically expanded by [27], who integrated the Tapio elasticity index with logarithmic mean Divisia index (LMDI) decomposition to demonstrate that carbon intensity and investment efficiency function as primary drivers of long-term sustainability. Concurrently, Refs. [28,29] explored the complex feedback loops of tourism eco-efficiency, utilizing advanced programming frontiers (EBM-ML super-efficiency) and panel vector autoregressions (PVAR) to prove that revenue expansion does not automatically safeguard the ecological environment.

While technically sophisticated, these carbon-decoupling metrics uniformly exhibit a significant planning blind spot. They operate under static geopolitical frameworks or within contiguous borders, failing to account for the structural transport distortions of international transit. By isolating aviation-induced CO₂ emissions across a synchronized global environmental panel ($n = 41$), this paper directly addresses the absolute carbon footprint of cross-border mobility, exposing the “Mass-Market Traps” where rapid nominal yield recovery masks aggressive environmental degradation.

2.3. Digital Nomadism, Visa Innovations, and Soft Infrastructure Accelerators

The post-pandemic acceleration of remote work has introduced a highly resilient traveler typology that challenges traditional destination management. Ref. [30] conceptualized this shift by formalizing the “nomatourist” paradigm, highlighting how the location-independent remote workforce utilizes sharing economy platforms to restructure the destination yield and expenditure dynamics. From a geographic standpoint, Ref. [31] mapped the emergent geographies of digital nomadism from a distinct “place perspective,” illustrating how remote professionals leverage geo-arbitrage to optimize high-income salaries against lower local living costs, while simultaneously warning of local inflationary strains and digital gentrification risks. To capture this segment, states have increasingly weaponized legal frameworks. Ref. [32] provided a comprehensive macro-assessment of digital nomad visas, revealing how nations utilize progressive immigration policy as a strategic lever for creative tourism development and talent acquisition.

Within the existing literature, these soft digital indicators are evaluated via isolated qualitative or conceptual lenses, with no empirical attempt to model them as dynamic covariates against physical connectivity. This study bridges this critical gap by extracting specialized digital market share metrics ($n = 18$) and directly testing them against traditional aviation centrality metrics (PageRank algorithms), providing an empirical baseline for digital leapfrogging.

2.4. Methodological Comparison Matrix

To visually demonstrate the explicit advantages, shared objectives, and distinct innovations of the proposed model, Table 1 systemically compares this study against the core literature with identical methodological or thematic tracks.

Table 1. Methodological and conceptual benchmarking matrix.

Target RQ Alignment	Study Reference	Primary Methodology	Sample Perimeter & Scale	Key Sustainability/Digital Indicator	Methodological Advantage of the Proposed Framework
RQ1	[24]	Hierarchical & K-Means Clustering	Local commune-level subsets (n = 66)	Composite recovery indicators mapping post-pandemic asymmetric pathways.	Scales the structural K-shaped recovery analysis across a global panel of 80 countries with heterogeneous income regimes.
RQ1 & RQ3	[25]	Unsupervised K-Means Cluster Analysis	Targeted urban destination sample (n = 20)	Workation suitability ranking based on infrastructure and local cost metrics.	Transforms static cluster profiles into dynamic policy simulations via a synchronized 2 × 2 Strategic Decision Matrix.
RQ2	[26]	Tapio Decoupling Index & Social Network Analysis (SNA)	Provincial panel data lines (n = 31)	Bottom-up calculated carbon spillovers and regional correlation networks.	Integrates scale-invariant decoupling indicators with unsupervised machine learning taxonomies across multiple analysis phases.
RQ2	[27]	Extended STIRPAT & Tapio-LMDI decomposition	Macroeconomic regional belt (11 major zones)	Tourism investment scale effects and historical carbon peak modeling.	Embeds demand-side digital nomad market share proxies to evaluate soft infrastructure accelerators alongside physical capital.
RQ2	[28]	Super-Efficiency EBM & Panel VAR (PVAR) diagnostics	Multi-period continuous panel (30 territories)	Interactive response tracking between eco-efficiency and economic growth.	Accounts for structural travel distortions by isolating international aviation Scope 3 constraints rather than generic domestic indicators.
RQ2	[33]	Tourism carbon emission modeling & input-output evaluation	Urban tourism consumption sectors (transport, sleep)	Sectoral carbon footprint intensity and environmental quality index vectors.	Operationalizes multi-sector indicators across a synchronized global panel with rigorous cross-border aviation controls.
RQ2	[34]	VOSviewer data mining & multiple-case structural tracking	772 bibliometric lines & 20 commercial mega-carriers	Critical constraints of corporate carbon disclosures and Paris Agreement targets.	Transforms macro airline supply boundaries into a scale-invariant environmental decoupling elasticity framework.
RQ2	[29]	Systematic literature mapping & bibliometric tracking	61 core publications on tourism eco-efficiency	Historical evolution of eco-efficiency metrics and conceptual core boundaries.	Transitions from retrospective literature aggregates to an active empirical deep-learning and decoupling engine.
RQ3	[31]	Place-centric geographical review	Secondary macro-geographic data lines	Geo-arbitrage mechanics, local inflation risks, and socio-spatial segregation.	Addresses the geographic data bias of Western datasets by isolating and validating the unique Type 4 African cluster (n = 8).
RQ3	[35]	Systematic literature review (PRISMA framework)	11 digital nomad market segment publications	Destination attraction factors, policy gaps, and regional workspace needs.	Rectifies the Sub-Saharan literature voids by explicitly modeling and validating the Type 4 African cluster (n = 8).
RQ3	[36]	Semantic content analysis & hierarchical network analysis	225 digital nomad destinations across global grids	Smart destination soft infrastructure adaptation and collaborative workplace ecosystems.	Evaluates the operational impact of soft branding metrics relative to pure topological physical connectivity metrics.
RQ3 & RQ4	[32]	Empirical policy mapping & thematic indexing	Global panel of active immigration frameworks	Strategic sovereign documentation of digital nomad visa policy objectives.	Quantifies qualitative visa policy constructs through active global market share metrics embedded in econometric estimations.

Table 1. *Cont.*

Target RQ Alignment	Study Reference	Primary Methodology	Sample Perimeter & Scale	Key Sustainability/Digital Indicator	Methodological Advantage of the Proposed Framework
RQ3 & RQ4	[37]	Qualitative thematic analysis & policy tracking	36 active digital nomad visa frameworks worldwide	Classification of immigration pathways (working tourists vs. talent attraction).	Quantifies qualitative policy classifications through empirical market share coefficients linked to recovery velocity.
RQ3 & RQ4	[30]	Conceptual tourist taxonomy	Secondary descriptive literature lines	“Nomatourist” behavioral traits and sharing economy revenue transformation.	Redefines conceptual nominal updates by tracking them through validated, empirical volume and yield recovery timelines across historical and post-crisis windows.
RQ3 & RQ4	[38]	Critical state-of-the-art literature synthesis	Macro-level lifestyle mobility and global travel networks	Intersections of geo-arbitrage, digital gentrification, and aviation hypermobility.	Directly tests conceptual gentrification and lifestyle markers against physical aviation network metrics using PageRank algorithms.

By contrasting these baseline coordinates, this study positions its dynamic core workflow around an integrated multi-tier sample funnel—encompassing the global macroeconomic panel ($n = 80$), the synchronized environmental sub-sample ($n = 41$), and the elite digital vanguard cohort ($n = 18$). Methodologically anchored in the parallel execution of K-Means clustering, scale-invariant Tapio decoupling elasticities, and exploratory Ordinary Least Squares (OLS) associative modeling, this specialized architecture provides the first unified framework capable of computing overlapping environmental constraints alongside dynamic digital vanguard brand indicators. Ultimately, this empirical integration demonstrates that post-crisis premiumization requires an active, strategic value-volume decoupling explicitly driven by soft digital infrastructure investments. Having firmly established these literature boundaries and structural gaps, the manuscript proceeds to detail the quantitative data harmonization engines, predictive models, and index engineering strategies within the subsequent research design.

3. Materials and Methods

3.1. Methodological Framework

To systematically address the complex interplay between economic resilience, environmental sustainability, and digital transformation, this study develops a multi-stage methodological pipeline, as shown in Figure 1. The research architecture follows a sequential progression from descriptive macroeconomic diagnostics to policy simulation. To maximize analytical transparency and provide a clear operational roadmap for the reader, the entire experimental workflow is formalized into six sequential computational steps:

Step 1: Data Ingestion and Multi-Tier Filtering. The processing pipeline commences with the ingestion of a comprehensive global baseline containing 212 countries and territories extracted from synchronized UN Tourism, OECD, and World Bank databases. A strict inclusion protocol is enforced to filter out missing records, establishing a structurally complete panel for subsequent analysis.

Step 2: Unsupervised Macroeconomic DNA Clustering (RQ1). The filtered indicators are scaler-standardized and utilized to feed a K-Means clustering algorithm configured at $k = 4$. (implemented via Python software, version 3.11, within the Google Colab cloud platform, utilizing the Scikit-learn library, version 1.3). This step identifies the core structural “DNA” of the destinations based on pre-crisis attributes, separating unique geo-graphic and economic regimes.

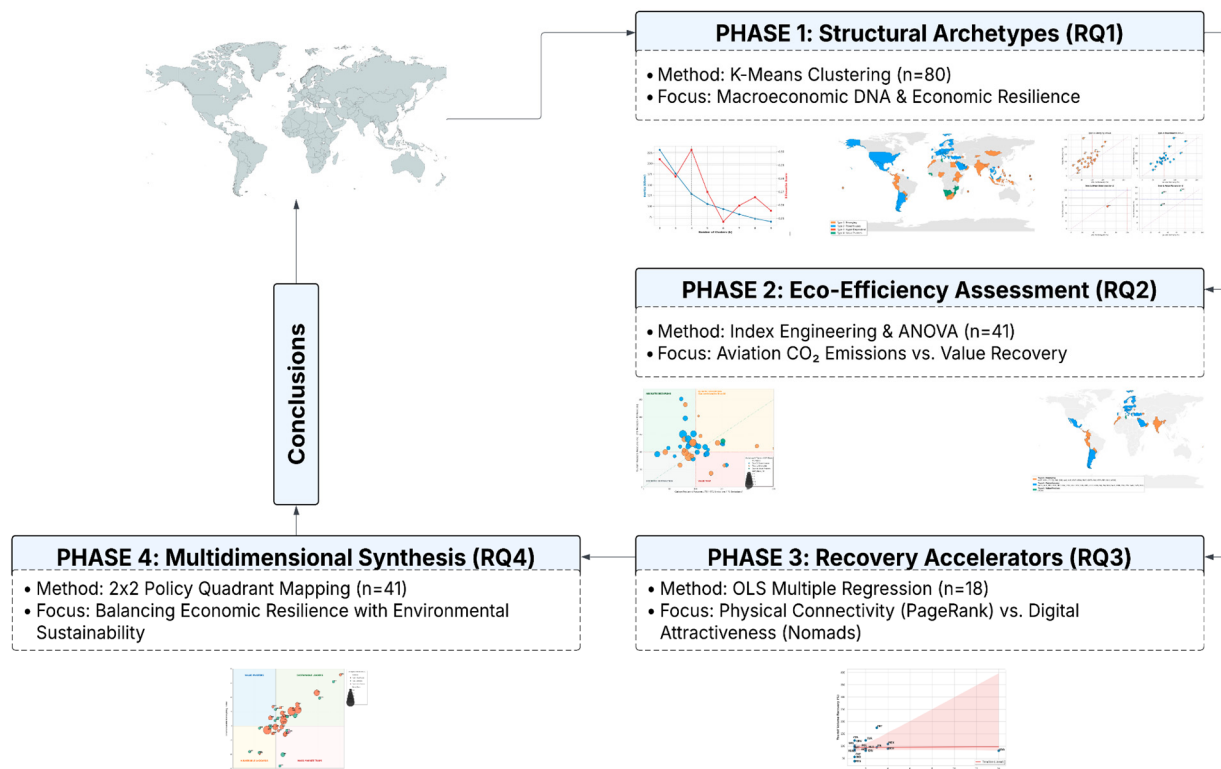


Figure 1. Methodological Framework illustrating the sequential progression of the four Research Questions (RQs) and their corresponding sample sizes.

Step 3: Post-Crisis Macroeconomic Resilience Evaluation (RQ1). Following cluster establishment, downstream post-pandemic data (2022–2024) are evaluated against the pre-crisis baseline (2015–2019). Three distinct resilience metrics, volume recovery (%), value recovery (%), and nominal yield growth (%), are computed per destination to map intra-cluster K-shaped trajectories.

Step 4: Carbon Emissions Boundary and Decoupling Indexes (RQ2). The sample is narrowed to a synchronized environmental sub-sample (n = 41) with verified aviation reporting lines. Environmental carbon costs are measured by multiplying per capita flight emissions by population aggregates, engineering scale-invariant Tapio decoupling elasticity indices (DE) to classify the destinations into Absolute, Relative, or Re-coupling trajectories.

Step 5: Associative Modeling of Dynamic Exogenous Accelerators (RQ3). Isolating an elite digital vanguard cohort (n = 18) where specialized global digital nomad market shares are documented, an exploratory Ordinary Least Squares (OLS) multiple regression model is specified. This model directly evaluates demand-side digital branding proxies against physical infrastructure network centrality (PageRank algorithms) to determine volume recovery velocity.

Step 6: Multidimensional Decision Simulation Matrix (RQ4). The synchronized environmental panel (n = 41) is projected into a unified two-dimensional strategic field. By enforcing theoretical thresholds from Step 3 (100% value recovery) and Step 4 (DE = 1.0), destinations are computationally assigned to one of four actionable policy zones, transforming quantitative outputs into localized strategic roadmaps.

3.2. Data Harmonization and Clustering Strategy (RQ1)

As a structural precondition for evaluating post-crisis trajectories, the objective of this initial module is to establish a rigorous global baseline typology by clustering heterogeneous national economies based on their pre-pandemic macroeconomic profiles.

A comprehensive data processing pipeline was developed, encompassing data harmonization, feature engineering, and unsupervised machine learning. To ensure maximum methodological transparency, a rigorous, multi-tier sample selection funnel was systematically applied across the distinct analysis phases of this study. The initial data ingestion commenced with a comprehensive baseline of 212 countries and territories documented within the UN Tourism and World Bank databases. For the primary macroeconomic clustering (RQ1), enforcing a strict protocol of complete, non-null observations strictly for the primary baseline clustering inputs (T0: 2015–2019) and the static Human Capital Index necessitated listwise deletion, establishing a final baseline panel of 80 global economies. Because the post-pandemic recovery metrics (T1: 2022–2024) were computed downstream and post-clustering, specific countries that exhibited asymmetrical reporting in the recovery window (e.g., reporting post-pandemic international receipts but missing arrival volume data) were deliberately retained to preserve the structural integrity of the macro-baseline panel. This localized reporting missingness in the downstream T1 vector accounts for the secondary N/A entries in the final descriptive table (Table A3) without violating the mathematical constraints of the initial K-Means algorithm. This core panel was subsequently refined to a synchronized sub-sample of 41 destinations for the environmental eco-efficiency analysis (RQ2), applying an exclusion criterion that omitted destinations lacking fully verified, non-interpolated aviation-induced CO₂ emissions reporting for the entire 2022–2024 recovery window. Finally, to evaluate the dynamic recovery accelerators (RQ3), the sample was narrowed to an elite digital vanguard cohort of 18 premier destinations, ensuring simultaneous data symmetry and availability for the specialized global digital nomad market share index. The annual time series for these destinations were harmonized into two distinct macroeconomic regimes by calculating the arithmetic mean: the Baseline Period (T0: 2015–2019), capturing the mature normality of global tourism, and the Recovery Period (T1: 2022–2024), utilized for the dynamic measurement of resilience.

To mitigate massive data attrition, variables were strictly stratified into two functional categories, as detailed in Table A1 in the Appendix A. The primary variables (Tourism GDP Share, Human Capital Index, Log10 of Arrivals, and Log10 of Yield) were utilized exclusively to feed the K-Means clustering algorithm (configured at $k = 4$), defining the structural “DNA” of the destinations. The selection of the K-Means partitioning algorithm over alternative unsupervised architectures, such as agglomerative hierarchical clustering, density-based methods (e.g., DBSCAN), or grid-based approaches, is dictated by the mathematical structure of the standardized macro-level panel. Hierarchical clustering is sensitive to initial distance linkage criteria and introduces structural inversion risks when segregating specialized macro-outliers, whereas density-based models rely on local density variations, rendering them ineffective for continuous, scaler-standardized economic indicators where clusters naturally display convex, hyperspherical geometries. Furthermore, grid-based algorithms are fundamentally optimized for multi-dimensional spatial database indexing, rather than geometric variance reduction across orthogonal indicators. By systematically minimizing the global within-cluster sum of squares (inertia), the K-Means algorithm guarantees a robust partitioning of continuous metric arrays while maintaining computational tractability and direct, multi-variable interpretability of the generated cluster centroids.

To prevent size bias driven by the absolute scale of countries, a Logarithmic Transformation (Log10) was applied to the volume of Arrivals and the derived Value-Added variable (Yield = Receipts/Arrivals). The data arrays were subsequently standardized to Z-scores using a standard scaler, ensuring that variables with disparate scales had equal influences on the algorithm’s geometric distance calculations. Before the clustering algorithm, a multicollinearity assessment was conducted to ensure that no single structural dimension was artificially over-weighted. The analysis evaluated the Variance Inflation

Factors (VIF) and Pearson correlation coefficients for all primary clustering variables. As detailed in Table A2 in the Appendix B, the highest observed correlation was between HCI and Log10 Arrivals ($r = 0.541$), which remains strictly below the conventional multicollinearity threshold of $r = 0.70$. Furthermore, all VIF values ranged from 1.04 to 1.68, confirming acceptable multicollinearity levels that are significantly below the strict conservative threshold of $VIF < 3$. This validates the orthogonal independence of the selected primary variables. Conversely, the secondary variables were integrated post-clustering. Their purpose was the descriptive profiling and economic validation of the generated archetypes, thereby preserving the final sample size.

Service quality and institutional resilience were evaluated using the composite Human Capital Index (HCI). The World Bank's HCI is a macroeconomic demographic metric, capturing national health, expected years of schooling, and survival rates, rather than a sector-specific measure of the hospitality labor supply. HCI values were at 2020 levels, representing the socio-economic stock. This filters out temporary sectoral labor shortages (e.g., the "Great Resignation" in hospitality), while capturing durable human capital endowments. Methodologically, utilizing the 2020 baseline as a static proxy rests on the structural property of macro-demographic stock variables, which exhibit intense path dependency and structural inertia. While the pandemic caused severe short-term flows and operational disruptions in education and healthcare globally, historical cross-country assessments demonstrate that the relative rank-order stability of national human capital endowments remains highly stable over short-term horizons (2020–2024). To eliminate multicollinearity, only the final composite index (scale 0–1) was utilized, excluding individual sub-indicators, while any unmeasured divergent shifts in post-pandemic human capital degradation are explicitly bound as an analytical limitation. Finally, metrics such as Average Length of Stay, Business-to-Personal Arrivals Ratio, and Domestic Hotel Guests were reserved as secondary profiling classifications and excluded from the primary clustering algorithm due to substantial missing data rates.

Following the establishment of the baseline structural archetypes, the post-pandemic resilience of each destination was quantified by comparing the Recovery Period (T1) against the Baseline Period (T0). Three primary resilience metrics were calculated: (a) volume recovery (%), defined as the ratio of T1 Arrivals to T0 Arrivals; (b) value recovery (%), defined as the ratio of T1 Receipts to T0 Receipts; and (c) yield growth (%), measuring the proportional change in value added per arrival between the two periods. These metrics allowed for a dynamic assessment of how different pre-crisis tourism models absorbed and reacted to the global shock. To mathematically verify that the K-Means algorithm generated structurally distinct and non-random archetypes, we conducted one-way Analysis of Variance (ANOVA) tests across the primary and secondary profiling variables. Effect sizes (Partial Eta-Squared, η^2) were also calculated to determine the magnitude of these differences. The Type 3 archetype (Macao) was excluded from the statistical analysis because it consists of only one observation ($n = 1$).

3.3. Environmental Accountability and Eco-Efficiency Analysis (RQ2)

To embed ecological parameters onto the established macroeconomic baselines, this module establishes a carbon efficiency boundary to identify whether financial destination recovery occurred at the expense of climate sustainability. The second phase of the analysis assessed the carbon footprint intensity and related environmental costs of tourism recovery by examining the emissions generated by international aviation. Methodologically, while a macro-level cross-border panel cannot capture localized ecosystem degradation or biodiversity loss, isolating international aviation greenhouse gases actively addresses the climate change vector—a primary pillar of UNEP's "triple planetary crisis" (com-

prising climate change, pollution, and biodiversity loss). Aviation constitutes the most carbon-intensive segment of the global tourism value chain, typically accounting for over 50% of direct tourism-related CO₂ emissions and serving as a critical proxy for assessing a destination's overall environmental pressure from international travel [39,40]. To evaluate environmental performance, annual per capita CO₂ emissions from international passenger flights were sourced from the OECD and Our World in Data (OWID). These values were multiplied by the World Bank's total annual population data to calculate total absolute CO₂ emissions (in metric tons). These absolute CO₂ emissions were averaged to construct the Baseline Period (T0: 2015–2019) and the Recovery Period (T1: 2022–2024), and synchronized with the panel of 80 destinations identified in RQ1 using ISO country codes to ensure cross-variable consistency. The specific data sources, computational formulas, and functional roles of the environmental variables are detailed in Table A1 in the Appendix A. Rather than analyzing the absolute emissions, which are inherently biased toward larger countries with a high number of arrivals, the study used the Environmental Efficiency (Eco-Efficiency). Eco-efficiency is defined as the economic value generated per unit of environmental degradation [41]. The following composite metrics were computed to address RQ2.

Carbon Footprint Recovery (%): Calculated as the ratio of T1 CO₂ emissions to T0 CO₂ emissions. This metric indicates whether a destination has returned to its pre-pandemic pollution levels. This approach aligns with recent efforts to track tourism-related emissions over time [39,40,42].

Tourism Eco-Efficiency (USD per ton of CO₂): Calculated by dividing Total International Tourism Receipts by Total Aviation CO₂ Emissions for both T0 and T1. This ratio serves as an “Environmental Yield,” indicating how many dollars a destination earns for every ton of carbon released into the atmosphere. The concept of expressing economic value per unit of pollution is consistent with UNEP's eco-efficiency framework [41] and with recent tourism decarbonization studies that use similar value-per-ton metrics [43].

Decoupling Index (DE): Moving beyond absolute differentials, the study operationalizes environmental efficiency using an elasticity framework, aligning with the Tapio standard and UNEP guidelines. DE is computed as the ratio of the logarithmic change in CO₂ emissions to the logarithmic change in Economic Value between the two periods: $DE = \ln(\text{CO}_2_T1 / \text{CO}_2_T0) / \ln(\text{Value_T1} / \text{Value_T0})$. This scale-invariant elasticity metric accurately classifies destination trajectories into distinct normative categories. In absolute decoupling ($DE < 0$, where $\text{Value} > 100\%$ and $\text{CO}_2 < 100\%$), economic value increases while absolute emissions decline (the optimal state). In weak/relative decoupling ($0 < DE < 1$), both metrics grow, but the economic value grows significantly faster than the emissions. The Value Trap/Recoupling occurs when CO₂ emissions increase despite or faster than economic recovery. This manifests in two sub-cases: (a) Expansive Value Trap ($DE > 1$), where revenue grows but emissions surge even faster, and (b) Collapse Value Trap ($\text{Value} < 100\%$, $\text{CO}_2 > 100\%$), where the destination faces environmental burden despite economic shrinkage. Lastly, in Economic Contraction, both economic value and emissions decline.

To mathematically evaluate whether environmental recovery outcomes differed systematically across the pre-pandemic structural archetypes, variance testing was conducted. Due to the highly skewed, non-normal distribution of the decoupling elasticity values (confirmed via a Shapiro–Wilk test, $p < 0.001$), the non-parametric Kruskal–Wallis H-test was deemed the appropriate statistical method for this cross-cluster comparison.

While the initial structural archetypes were identified from a panel of $n = 80$ countries (RQ1), the environmental efficiency analysis (RQ2) was restricted to a refined sub-sample of $n = 41$ destinations. A destination was retained only if it possessed complete, non-null reporting for both international tourism receipts and aviation-related CO₂ emissions for the

full T1 recovery period (2022–2024). This filtering ensured that all calculated Decoupling Indices and Eco-Efficiency metrics were grounded in verified empirical datasets rather than interpolations. Consequently, the refined sample predominantly comprises developed and rapidly emerging economies with robust environmental reporting infrastructures. Notably, the Type 4 archetype (Value Pivoters) is represented by a single destination (Tunisia), thereby limiting the generalizability of the environmental decoupling patterns for this structural cluster. This limitation on sample size poses a distinct methodological constraint, as the environmental metrics calculated for this quadrant reflect an isolated, destination-specific trajectory, rather than a statistically validated representation of the entire Type 4 cohort. Consequently, subsequent insights regarding this zone are treated as a descriptive case study of Tunisia’s localized post-crisis trade-offs rather than a generalized cluster wide behavior.

3.4. Recovery Accelerators: Network Infrastructure and Digital Attractiveness (RQ3)

Recognizing that static baseline capacities are actively modulated by dynamic post-crisis forces, the objective of this econometric module is to isolate the predictive behavior of physical route infrastructure against soft digital brand equity. While structural archetypes (RQ1) comprehensively capture a destination’s macroeconomic baseline (GDP per capita, HCI, yield, and tourism dependence) and eco-efficiency (RQ2), the post-pandemic literature posits that exogenous, dynamic forces also drive recovery velocity. Recent studies identify two distinct dimensions of accessibility as primary catalysts for post-pandemic resilience: physical connectivity, operationalized through aviation networks, and digital attractiveness, characterized by remote-work readiness and contemporary brand appeal [41,44–46]. To empirically test the association of these distinct accelerators with recovery, the methodology for RQ3 integrated Network Science and global mobility data.

Rather than relying on degree centrality metrics (e.g., total flight counts), the study evaluated global air connectivity using the PageRank algorithm. To reflect the post-pandemic structural reality, the network was constructed as an unweighted, undirected topology using the updated 2023 global aviation dataset. While passenger flow volumes or specific flight frequencies can exhibit directional asymmetries at the micro level, aggregating the network to a macro-level, country-to-country topological grid justifies an undirected specification. International commercial aviation operates fundamentally on reciprocal bilateral air service agreements, meaning that if a scheduled commercial flight connection is established from Country A to Country B, a symmetric return route is structurally maintained to reposition aircraft and sustain operational schedules. Consequently, an undirected topology serves as a robust, stable proxy for macro-systemic accessibility and route infrastructure availability without introducing extraneous noise from localized or seasonal directional flows. The algorithm was executed computationally via NetworkX library (version 3.2) within a Python environment (version 3.11) hosted on the Google Colab cloud platform, applying the standard damping factor of $d = 0.85$. PageRank measures the transitive importance of a destination. A country achieves a high score not merely by having many flight connections, but by being directly connected to other highly central global hubs.

To operationalize a destination’s digital reputation and attractiveness robustly, the study utilized the global Digital Nomad Market Share (%) [47]. Digital nomads represent a highly resilient, high-yielding segment of modern travelers whose destination choices are strictly governed by digital infrastructure, internet speed, cost of living, and perceived lifestyle quality. Thus, a destination’s global market share of digital nomads serves as a quantifiable proxy for its overarching digital brand equity. It is acknowledged that the Statista dataset may exhibit a US-centric geopolitical preference bias. Specifically, because this digital nomad variable is derived from a predominantly US-weighted survey

instrument, it carries an inherent structural bias that may overrepresent Anglophone destination preferences, serving as an early methodological caveat for the reader. However, it remains the most comprehensive standardized metric currently available for digital nomad global distribution.

To quantify the associative power of these accelerators, an Ordinary Least Squares (OLS) multiple regression model was specified. The dependent variable was defined as tourist volume recovery (Vol_Rec_pct). To ensure scale comparability, both PageRank and Digital Nomad Share predictors were standardized into Z-scores. To maintain variance integrity and avoid artificial imputations, the regression was executed on a synchronized sub-sample ($n = 18$) of highly ranked global destinations where simultaneous, non-null data across all dimensions were available. These destinations represent the global digital attractiveness, capturing early-adopter markets. Consequently, insights derived from this sub-sample are explicitly reframed as applicable strictly to the structural configurations of Type 1 and Type 2 destinations, which constitute 100% of the active digital cohort. Given the complete absence of Type 3 and Type 4 archetypes from this subset due to severe data missingness, the regression results cannot evaluate whether these highly specialized or constrained economies would systematically benefit from identical digital strategies. Therefore, the statistical signals are utilized as a bounded heuristic baseline for mature and emerging markets, rather than a universal deterministic law across all structural archetypes.

Although the OLS regression captures robust statistical associations, it cannot prove unidirectional causality. Profound endogeneity and reverse causality shape the relationship between digital attractiveness and tourism recovery indicators. For instance, while destinations with high digital brand equity actively attract remote workers, locations with established high-yield infrastructure and premium lifestyle metrics are inherently better positioned to capture the global digital nomad market. These parameters operate as dynamic, mutually reinforcing covariates rather than strict unidirectional causal vectors. Therefore, this structural interdependence restricts the OLS regression model in Equation (1) to an exploratory, associative tool.

$$\text{Volume_Recovery}_i = \beta_0 + \beta_1(\text{PageRank}_i) + \beta_2(\text{Nomads}_i) + \gamma(\text{Archetypes}) + \delta(\text{Log_Passengers}) + \varepsilon_i \quad (1)$$

The β_1 and β_2 isolate the main effects of physical and digital accessibility, respectively. The $\gamma(\text{Archetypes})$ acts as a categorical control variable to account for the baseline structural fixed effects identified in RQ1, and $\delta(\text{Log_Passengers})$ controls for the absolute baseline volume of the aviation market (2019 baseline).

It does not attempt to establish definitive causal links; rather, its primary empirical utility is to isolate a joint, multi-dimensional signal within a tightly bounded sample ($n = 18$), treating these parameters as overlapping dimensions of a destination's modern accessibility profile. A comprehensive summary of all variables, data sources, and their specific functional roles within this exploratory framework is detailed in Table A1 in the Appendix A.

3.5. Synthesis and Strategic Decision Matrix Framework (RQ4)

The final phase of the methodology establishes a synthesis of the multidimensional findings derived from the structural archetypes (RQ1), ecological accountability (RQ2), and recovery accelerators (RQ3). This framework transitions the study from descriptive diagnostics to policy simulation, providing a structured roadmap for sustainable tourism transitions. The core of this synthesis is the construction of a Strategic Decision Matrix, operationalized through a multi-step computational pipeline. The specific variables, calcu-

lation formulae, and their functional roles within this synthesis are detailed in Table A1 in the Appendix A.

To formalize the structural interaction within the mathematical pipeline, the inter-dependent roles and analytical weights of the individual research stages within the final calculation decision matrix are codified using a deterministic coupling logic: (1) RQ1 (economic resilience/value recovery) functions as the primary horizontal positioning coordinate, commanding an absolute spatial weight of 50% for quadrant assignment. (2) RQ2 (Environmental Sustainability/Decoupling Index) serves as the primary vertical positioning coordinate, dictating the remaining 50% of the spatial weighting matrix. (3) RQ3 (Digital Destination Attractiveness/Nomad Share) is mapped as the multi-dimensional Z-axis (bubble volume), operating not as a static coordinate weight, but as a dynamic strategic multiplier that calculates the destination's evolutionary leverage for horizontal quadrant migration. (4) RQ4 functions as the final integrative synthesis and policy simulation layer that aggregates these weighted vectors into the unified decision engine. For visual completeness within the multi-task pipeline, the 18 elite destinations utilize empirical nomad market shares to dictate the bubble volume, while the remaining 23 destinations utilize a standardized baseline placeholder value.

To ensure conceptual clarity, the four strategic quadrants are formalized based on their strict macroeconomic and ecological boundary conditions at the intersection of the 100% value recovery and Tapio-aligned $DE = 1$ standardized thresholds: (1) Sustainable Leaders ($Value \geq 100\%$, $DE < 1$) represent the optimal eco-efficient paradigm in which absolute or relative carbon decoupling coexists with robust financial growth. (2) Mass-Market Traps ($Value \geq 100\%$, $DE > 1$) characterize carbon-intensive growth models in which rapid volume recovery masks severe underlying atmospheric vulnerabilities. (3) Value Pivoters ($Value < 100\%$, $DE < 1$) identify quality-driven niche frameworks that sacrifice absolute revenue speed to enforce strict ecological containment. (4) Vulnerable Laggards ($Value < 100\%$, $DE > 1$) reflect absolute systemic friction, trapped in a dual crisis of economic contraction and persistent carbon loading. In terms of modeling execution, these concepts operate as discrete classification anchors that translate highly non-linear, multi-variable empirical data into standardized, actionable strategic trajectories.

3.6. Model Characteristics: Universality, Robustness, and Portability

The mathematical stability of the proposed computational architecture relies on the integration of robustness, universality, and portability. Robustness is guaranteed through listwise deletion, log-transformations, and standard Z-score scaling to eliminate size bias driven by the absolute destination scale, supported by a Variance Inflation Factor ($VIF < 3$) screening that preserves variable orthogonality. Universality is achieved by utilizing scale-invariant, non-parametric Tapio decoupling elasticity formulas that maintain statistical stability across disparate economic regimes and highly skewed datasets. Consequently, the model exhibits strong portability within the strategic decision matrix because it maps classification metrics to relative standardized thresholds, namely the 100% financial recovery and $DE = 1$ boundaries, rather than case-specific values. This integrated design ensures that the analytical pipeline can be seamlessly transferred to alternate global shocks, extended policy horizons, or sub-national destination layers.

4. Results

4.1. RQ1: Structural Archetypes and Resilience Dynamics

4.1.1. Unsupervised Cluster Validation and Data Funnel

The analysis was predicated on UN Tourism data exhibiting retention rates of 100% for Receipts ($n = 212$ countries) and 99.1% for Arrivals ($n = 206$ countries). To ensure con-

sistency and mitigate temporal volatility, an explicit aggregation protocol was applied, transforming the annual time series into period averages for the baseline (T0) and recovery (T1) phases. The intersection of this dataset with macroeconomic indicators (Tourism GDP Share and HCI) necessitated the deletion of countries, generating a final, fully harmonized panel of 80 global economies. The determination of the optimal number of clusters (k) was mathematically validated using heuristic criteria. As depicted in Figure 2, while the Silhouette score reached its peak at $k = 3$, the Elbow method (inertia) exhibited a clear inflection point at $k = 4$, indicating the optimal reduction in within-cluster variance. Consequently, the $k = 4$ solution was selected, as it balanced this mathematical validation with interpretability and structural granularity. Specifically, $k = 4$ isolated statistical outliers with extreme tourism dependence (Type 3) and distinguished niche developing markets (Type 4) from the broader emerging cluster, thereby preventing the dilution of archetype-specific characteristics. Relying strictly on the global Silhouette maximum at $k = 3$ would introduce significant structural compression, forcing macroeconomically unique clusters to merge. The Elbow method's distinct inflection point at $k = 4$ effectively captures the critical reduction in a within-cluster sum of squares (inertia) while preventing the dilution of specialized economic pathways. Retaining $k = 4$ mathematically isolates Macao as an extreme, hyper-dependent monoculture (Type 3) and preserves the distinct identity of the African niche developing markets (Type 4), both of which would otherwise be absorbed into broader cohorts.

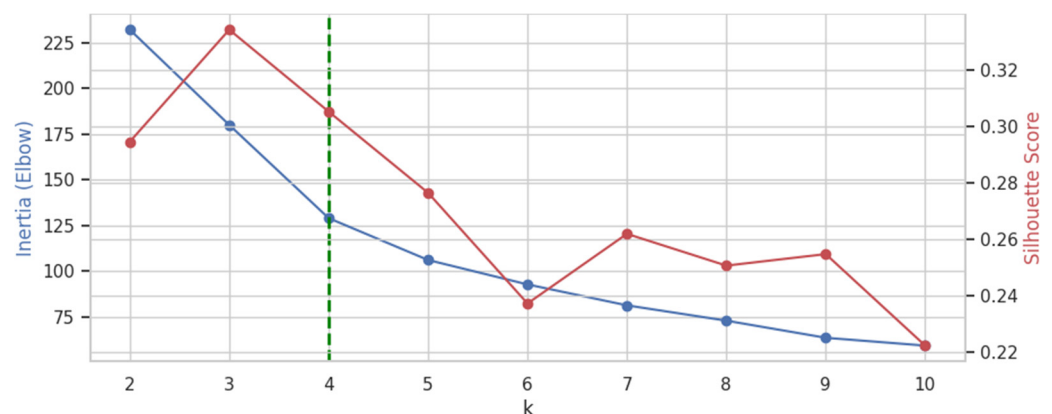


Figure 2. Optimal cluster selection (Elbow Method & Silhouette).

4.1.2. Macroeconomic Profiles of the Four Distinct Archetypes

The application of the K-Means algorithm ($k = 4$) led to the identification of four strategic groups. As detailed in Table 2, the foundational baseline variables defining the pre-pandemic structures, notably Yield T0 ($F = 11.5$, $p < 0.001$), HCI ($F = 68.9$, $p < 0.001$), and the baseline Length of Stay (LOS T0) ($F = 5.0$, $p = 0.011$), exhibited highly significant between-cluster variance with robust effect sizes. This definitively confirms the distinct structural DNA of each archetype, statistically validating, for instance, the disparity between long-haul experience-centric hubs and high-velocity transit destinations. Conversely, the variance in post-pandemic recovery metrics was not statistically significant between the clusters ($p > 0.05$), indicating that pre-pandemic macroeconomic structures did not deterministically dictate the recovery trajectory. To evaluate the statistical power of these non-significant tests under conditions of highly unequal cluster sizes ($n = 33, 38, 1, 8$), partial eta-squared (η^2) effect sizes were computationally derived. The analysis yielded a small-to-medium effect size for tourist volume recovery ($\eta^2 = 0.0772$, $F = 1.645$, $p = 0.1886$) and a small effect size for value recovery ($\eta^2 = 0.0306$, $F = 0.757$, $p = 0.5219$). This confirms that while the parametric tests face structural power constraints due to the unavoidable macro-level data attrition of specific destination cohorts, the absolute magni-

tude of variance explained by the pre-crisis archetypes remains profoundly low. Rather than a limitation, this empirically validates the core hypothesis of intra-cluster heterogeneity: while pre-pandemic macroeconomic structures define the theoretical archetypes, they did not deterministically dictate the recovery trajectory, which was ultimately driven by localized exogenous factors and agile policy pivots. The global spatial distribution of these structural baselines is illustrated in Figure 3, revealing distinct regional clustering, while their aggregate macroeconomic profiles are summarized in Table 2 (the comprehensive list of countries per archetype is detailed in Table A5 in the Appendix B).

Table 2. Aggregate profile, resilience indicators, and ANOVA results.

Indicator/Variable	Type 1: Emerging (n = 33)	Type 2: Powerhouses (n = 38)	Type 3: Hyper-Dep. (n = 1)	Type 4: Pivoters (n = 8)	F-Stat	p-Value	η^2 (Effect Size)
GDP Share T0 (%)	4.8	4.8	49.9	3.1	0.9	0.400	0.02
Yield T0 (\$)	1806.6	1075.0	2156.8	217.9	11.5	0.001 ***	0.23
HCI T0 (0–1)	0.5353	0.69	0.80	0.41	68.9	0.001 ***	0.64
LOS T0 (days)	6.0	3.0	1.5	4.0	5.0	0.011 *	0.18
LOS T1 (days)	5.4	2.9	1.8	3.1			
Volume Recovery (%)	82.1	97.1	64.7	60.2	2.3	0.114	0.07
Value Recovery (%)	113.3	114.6	57.8	95.6	0.5	0.597	0.01
Yield Growth (%)	76.1	23.9	−10.6	97.1	1.9	0.155	0.06
Labor Change (%)	−17.4	−4.3	−22.8	−6.5	1.0	0.367	0.06
LOS Change (%)	15.8	3.6	24.3	17.3	0.9	0.403	0.05

Note: * and *** indicate statistical significance at the $p < 0.05$ and $p < 0.001$ levels, respectively; η^2 denotes the effect size (eta-squared). Type 3 (Macao) was excluded from the ANOVA calculations as it consists of only one observation ($n = 1$). LOS Change (%) is calculated globally at the country level using the formula $[(\text{LOST1} - \text{LOST0}) / \text{LOST0}] \times 100$ and then averaged per archetype. Labor Change (%) and LOS dynamics were computed on a restricted sub-sample due to missing post-pandemic reporting by UN Tourism. Values reported for Yield T0, Yield T1, and Yield Growth (%) are calculated in nominal USD; real growth rates may differ due to the asymmetric global inflationary shocks of the 2022–2023 period.

Map 1. Global distribution of the four structural tourism archetypes (Baseline: 2015–2019).

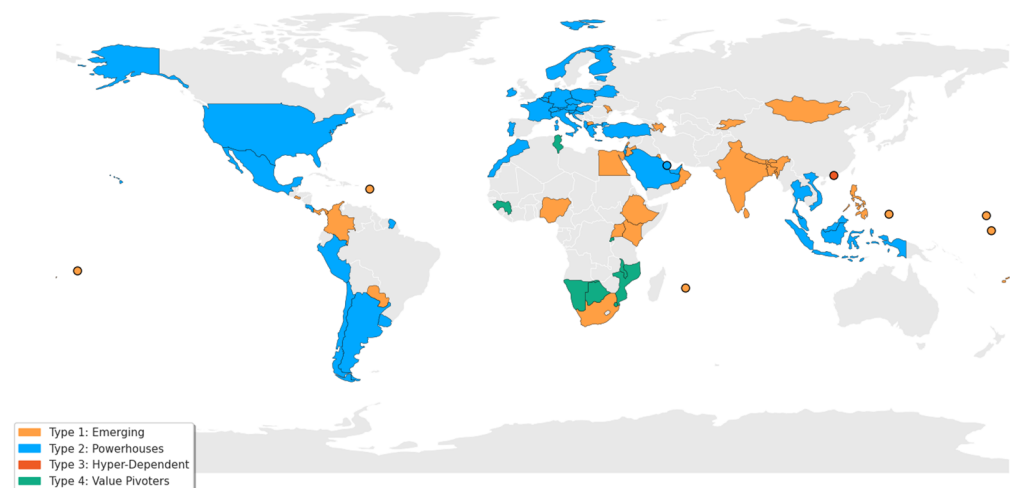


Figure 3. Global distribution of the four structural tourism archetypes (Baseline: 2015–2019). Note: The map displays the full sample of classified destinations ($n = 80$). To ensure comprehensive spatial representation, microstates and Small Island Developing States (e.g., Fiji, Mauritius, Macao) whose polygonal geometries are not visible at this global resolution are plotted using color-coded centroid markers.

To comprehensively address the profound structural shifts in service capacity, often conceptualized as the post-pandemic “Great Resignation” in hospitality, the study cross-examined the established baseline archetypes with UN Tourism employment data (individuals employed in tourism-related industries per 1000 people). To resolve data fragmentation and staggered national reporting cycles, post-pandemic labor density was

calculated as the 2022–2023 period average. Despite this temporal aggregation, the synchronized sample was restricted to only 38 out of 80 countries. This limitation strictly prevented the inclusion of sectoral employment as a primary K-Means clustering variable, as it would have necessitated a 52.5% sample attrition. However, its utilization as a secondary profiling diagnostic strongly validates the underlying yield hypothesis.

Specifically, the analysis reveals a universal contraction in tourism labor density across all structural archetypes. Emerging destinations (Type 1) and the Hyper-Dependent market (Type 3) experienced the most severe workforce density reductions of 17.4% and 22.8%, respectively. This universal contraction aligns with recent industry studies indicating a projected global shortfall of 43.1 million tourism workers by 2035, driven by demographic shifts and evolving work preferences [48]. Furthermore, empirical evidence from European labor markets demonstrates that post-pandemic recovery exposed deep-seated structural vulnerabilities, such as high rates of informality and reliance on precarious, seasonal contracts, which significantly hindered workforce retention [49]. Crucially, mature Powerhouses (Type 2) and Value Pivoters (Type 4) also recorded notable labor contractions of 4.3% and 6.5%. Yet, despite this reduced workforce, Type 2 achieved the highest overall value recovery (114.6%), while Type 4 recorded the most explosive yield growth (97.1%). This empirically confirms that post-pandemic premiumization is intricately linked to labor optimization, generating superior financial returns with a significantly contracted service workforce. As the [48] emphasizes, mitigating such acute labor deficits requires a strategic pivot toward digital upskilling and operational automation, enabling destinations to maintain high-yield service standards with leaner teams. Ultimately, this substantiates the sectoral constraints of the “Great Resignation” while methodologically defending the use of the static 2020 Human Capital Index (HCI) as a more reliable proxy for baseline structural profiling.

Type 1—The Long-Haul Emerging Markets (n = 33): Despite the cluster label, this diverse group spans multiple income levels (from Luxembourg at \$91,632 GDP per capita to Kyrgyzstan at \$3741). What unifies them is not income per se, but their reliance on long-haul arrivals, diversified tourism offerings, and strategic positioning outside established global tourism cores. This cluster represents a dynamic, globally dispersed tapestry of developing and niche economies. Its core is predominantly anchored in Asia (Azerbaijan, Bangladesh, Bhutan, India, Jordan, Kyrgyzstan, Kuwait, Lebanon, Sri Lanka, Mongolia, Nepal, Oman, the Philippines) and Africa (Egypt, Ethiopia, Kenya, Mauritius, Nigeria, Uganda, South Africa). Its geographical footprint is further diversified by Small Island Developing States (SIDS) in Oceania (Fiji, Kiribati, Marshall Islands, Palau, Samoa), alongside strategic emerging markets in North/Central America (Antigua and Barbuda, Panama, El Salvador), Europe (Luxembourg, Moldova, North Macedonia), and South America (Colombia, Paraguay).

Overall, this group experienced tangible macroeconomic progress during the recovery phase, functioning primarily as “experience-centric” long-haul destinations with the sample’s longest average stays. While the cluster exhibited a collective upward trajectory, intra-cluster variance vividly illustrates the impact of localized geopolitical and structural shocks. At the upper echelons of growth, nations like Mongolia and Ethiopia recorded immense relative wealth convergence, achieving a 49.8% and 52.4% surge in their GDP per capita, respectively. Concurrently, energy-exporting nations (Kuwait, Oman) emerged as absolute economic beneficiaries, capitalizing on the 2022–2024 global energy price surge. Conversely, profound structural crises severely derailed specific markets. Lebanon suffered a dramatic 58% contraction in GDP per capita, and Sri Lanka experienced a 7.7% decline, directly mirroring their respective unprecedented sovereign defaults and socio-political instability during the 2022 recovery window. Similarly, within the SIDS subgroup, Palau,

a premium, tourism-dependent economy, faced a 10.2% economic contraction due to frozen international aviation networks, starkly contrasting with the resilience seen in less tourism-reliant islands like Samoa (+13.2%). Destination-level behavior in this cluster shifted dramatically in alignment with post-pandemic consumer trends. Nations like Panama and the Philippines experienced explosive growth in their Length of Stay (LOS), practically doubling their baselines (Panama increased from 4.2 to 8.0 days, and the Philippines from 2.5 to 5.0 days). This structural lengthening of itineraries strongly correlates with the global phenomena of “revenge travel” and “blended/bleisure travel” (the fusion of remote work and leisure), where tourists opted for fewer but significantly longer journeys. Consequently, for nations like Panama, this prolonged LOS catalyzed a structural tourism upgrade directly linked to substantial per capita income growth. In stark contrast, destinations plagued by macroeconomic instability struggled to retain tourists. Sri Lanka’s LOS declined by 11.2%, an operational consequence of severe domestic shortages in fuel and electricity during its 2022 crisis, which forced early departures. Even more dramatically, Lebanon, already operating on a brief 3.2-day LOS, saw further compression to 3.0 days. Despite these localized crises, Type 1 spearheaded the global trend toward nominal premiumization. As a cluster, it achieved an exceptional average yield growth of 76.1% (measuring the increase in tourism revenue per arrival). While a portion of this yield expansion inevitably absorbs the baseline inflationary shifts in the post-pandemic market, the scale of this growth reflects an aggressive nominal decoupling of economic value from tourist volume, driven by targeted adjustments in destination pricing strategies.

Type 2—The Resilient Powerhouses (n = 38): This archetype forms the structural and financial backbone of the global tourism industry. It is overwhelmingly anchored in Europe (Albania, Austria, Belgium, Belarus, Switzerland, Czechia, Germany, Estonia, Finland, France, Greece, Croatia, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Slovenia), which dictate the cluster’s high-income macroeconomic profile, supported by major tourism superpowers in North America (Costa Rica, Mexico, United States). This traditional core is strategically diversified by high-connectivity aviation hubs in Asia (Bahrain, Hong Kong, Indonesia, Israel, Malaysia, Saudi Arabia, Thailand, Turkey, United Arab Emirates, Vietnam) and emerging structural leaders in Latin America (Argentina, Chile, Peru, Uruguay) and Africa (Morocco).

Overall, this group represents the highest wealth concentration in the sample, with the European contingent’s average GDP per capita accelerating from \$35,684 in T0 to \$45,594 in T1. Although the cluster encompasses ultra-wealthy economies (e.g., Ireland: \$108,301; Switzerland: \$99,672; USA: \$80,741), its defining characteristic is universal macroeconomic growth across completely different baselines. Central and Eastern European nations demonstrated explosive relative convergence, with Czechia (\$30,622, +45.3%), Estonia (\$30,010, +43.1%), and Poland (\$22,046, +56.3%) recording massive income growth. Similarly, developing regional giants like Mexico (\$13,150, +33.6%) and Peru (\$7896, +18.9%) proved that immense tourism scale and high institutional quality can act as structural equalizers, allowing macroeconomically disparate nations to share the same operational resilience model. In contrast to the extended, leisure-focused stays of the Emerging Markets (Type 1), the Powerhouses operate on a strictly high-frequency, high-volume model. The Length of Stay (LOS) is intensely compressed. During the recovery period, the subset of European destinations within Type 2 maintained an exceptionally low average of 2.39 days (with major hubs like the Netherlands and Finland operating under 2 days), while South American nations lowered sharply from 2.59 to 2.15 days. Across the entire Type 2 archetype globally, the average LOS stood at 2.9 days in T1, reflecting the inclusion of Asian hubs with slightly longer transit stays. While the global post-pandemic trend favored longer “bleisure” trips (revenge travel), Type 2 resisted this shift, recording marginal decreases in LOS instead.

This brevity structurally confirms their status as highly accessible global aviation hubs, dominated by short-term “city breaks,” corporate travel, and high-velocity cross-border mobility (particularly within the Schengen area). The European core boasts Human Capital Index (HCI) scores approaching 0.80 (e.g., Finland at 0.796, Ireland at 0.793, Netherlands at 0.790). This reflects superior healthcare, education, and transport infrastructure, acting as a safety net. Despite relying on high visitor volumes and constant mobility (a model theoretically highly vulnerable to pandemic restrictions), this cluster demonstrated the highest systemic stability globally. They completely absorbed inflationary shocks organically, successfully translating a massive volume recovery (97.2%) with minimal workforce attrition (−4.3%) into robust financial resilience (+23.9% yield growth), cementing their role as the ultimate stabilizers of global tourism.

Type 3—The Hyper-Dependent (n = 1): Represented exclusively by Macao (East Asia), this archetype is an extreme statistical outlier organically isolated by the K-Means algorithm, serving as a scientific benchmark for tourism over-specialization. It is critical to clarify that Type 3 is a single-observation archetype (n = 1), meaning its structural configuration is highly idiosyncratic to Macao’s specific geopolitical and socio-economic framework. Rather than functioning as a statistically generalizable cluster designed to describe a broad cohort of destinations, Type 3 operates methodologically as a unique structural anomaly and an empirical boundary condition for absolute tourism monoculture. While other hyper-dependent Small Island Developing States (such as the Maldives) share high tourism-to-GDP ratios, Macao’s extreme geometric isolation within the K-Means algorithm is driven by its unparalleled combination of hyper-dense casino capitalization and massive localized receipts. Consequently, Type 3 is explicitly not intended to generalize beyond this single case, but serves as a theoretical anchor point to evaluate the extreme outer limits of structural specialization within the global tourism matrix. Macroeconomically, it belongs to the global wealth elite; however, its economic backbone is characterized by an unprecedented and precarious structural reliance, with tourism directly contributing a staggering 49.9% to its total GDP. This represents the highest dependency ratio in the entire global sample, illustrating a profoundly monolithic economic structure. Operationally, Macao relies on a massive-volume but fleeting-duration paradigm. Before the pandemic, it absorbed tens of millions of arrivals, yet its Length of Stay (LOS) was strictly compressed to a mere 1.5 days, the lowest absolute value recorded globally. This extreme brevity unmasks the core nature of its tourism product, which is a highly specialized “casino-tourism” hub heavily dependent on day-trippers and short weekend getaways, originating almost exclusively from neighboring mainland China and Hong Kong. Unlike Type 1, Macao functions purely as a high-velocity consumption center. This archetype provides the most compelling empirical evidence regarding the systemic perils of tourism monoculture. Despite its accumulated wealth and institutional capacity, its hyper-dependence triggered a structural collapse during the recovery phase (T1). The sector’s workforce density severely contracted by −22.8%, marking the sharpest labor drain globally. More critically, Macao became entrapped in a post-pandemic “value trap.” While all other clusters (Types 1, 2, and 4) successfully capitalized on the global “premiumization” trend by increasing their yield, Macao was the sole archetype to record a structural depreciation of its tourism product. With arrival volume recovery stalling at 64.7% and economic value recovery lagging even further at 57.8%, its overall yield contracted by −10.6%. This confirms that rigidly monothematic, volume-dependent tourism models are vulnerable to global mobility shocks, lacking the structural elasticity required to pivot or upgrade their value proposition during a prolonged systemic crisis.

Type 4—The Strategic Value Pivoters (n = 8): In contrast to the geographically dispersed archetypes, this cluster possesses absolute continental cohesion, represented ex-

clusively by eight African nations (Botswana, Guinea, Mozambique, Malawi, Namibia, Rwanda, Eswatini, and Tunisia). Macroeconomically, this group occupies the lowest income bracket of the global sample, with the average GDP per capita rising from \$2730 in T0 to \$2979 in T1. Nations like Guinea (nearly doubling its GDP per capita from \$851 to \$1555) and Rwanda (from \$760 to \$1000) recorded impressive relative growth, while Botswana (\$7950) stands out as the cluster's most robust economy, functioning as a regional anchor of stability. What structurally unifies these nations is not merely their geography, but their severe constraints in human and institutional capital. Bound by an average Human Capital Index (HCI) of 0.409, the lowest in the study, and historically depressed revenue generation (with a baseline yield of just \$218 per arrival), these destinations operated primarily as low-cost, exploratory, or volume-dependent regional markets pre-pandemic. During the post-pandemic phase, the Length of Stay (LOS) within this cluster underwent a notable compression, declining from an average of 3.84 to 3.09 days. Traditional volume-driven destinations like Tunisia recorded LOS contractions (from 5.54 to 4.70 days), while destinations like Eswatini maintained exceedingly brief stays (1.48 days). This compression strongly indicates a reliance on intra-regional border crossings or highly targeted, short-duration travel (e.g., brief safari excursions), rather than the prolonged "bleisure" stays observed in Type 1. These nations endured a severe volume shock, recovering a mere 60.2% of their baseline tourist arrivals. However, they achieved near-total revenue parity (95.6% value recovery). This extraordinary resilience was engineered through an aggressive "volume-value decoupling" strategy, practically doubling the value added per tourist (+97.1% yield growth). These data unveil a phenomenon of "forced premiumization": constrained by pandemic-induced systemic shocks and lacking the massive infrastructural safety nets of mature markets, these African destinations were compelled to abandon the low-yield model. Instead, they strategically pivoted toward niche, higher-margin tourism segments.

4.1.3. Asymmetric K-Shaped Post-Crisis Resilience Quantifications

The evaluation of resilience (Period T1 versus T0) confirms a profoundly asymmetric "K-shaped" recovery trajectory, as visualized in Figure 4. The "Resilient Powerhouses" (Type 2) demonstrated robust macro-resilience, recovering their arrival volume almost entirely (97.2%) and significantly surpassing their pre-pandemic revenues (114.6%), thereby organically absorbing global inflationary pressures through a positive yield growth of 23.9%. However, significant intra-cluster heterogeneity exists within this group. Regional leaders, such as Saudi Arabia (+251.6% value recovery) and Albania (+229.8%), vastly outperformed traditional mature markets by leveraging aggressive tourism diversification and infrastructure investment strategies. Conversely, destinations affected by prolonged health protocols or geopolitical instability, such as Hong Kong (40.0% value recovery) and Israel (62.4%), severely lagged. At the extreme negative end, the "Hyper-Dependent Monoculture" (Type 3—Macao) collapsed, recording a structural depreciation of its tourism product (−10.6% in yield).

Another striking finding emerges from Type 4 (Value Pivoters). Although this cluster recovered only 60.2% of its baseline volume, it almost fully recovered its revenues (95.6%). This was achieved through an impressive volume-value decoupling strategy, nearly doubling the value added per tourist (yield growth: +97.1%). A prime example is Eswatini, which achieved a 122.2% value recovery driven by an explosive 161.3% growth in yield. This suggests that the pandemic forced a strategic pivot away from mass tourism, toward niche, higher-margin segments.

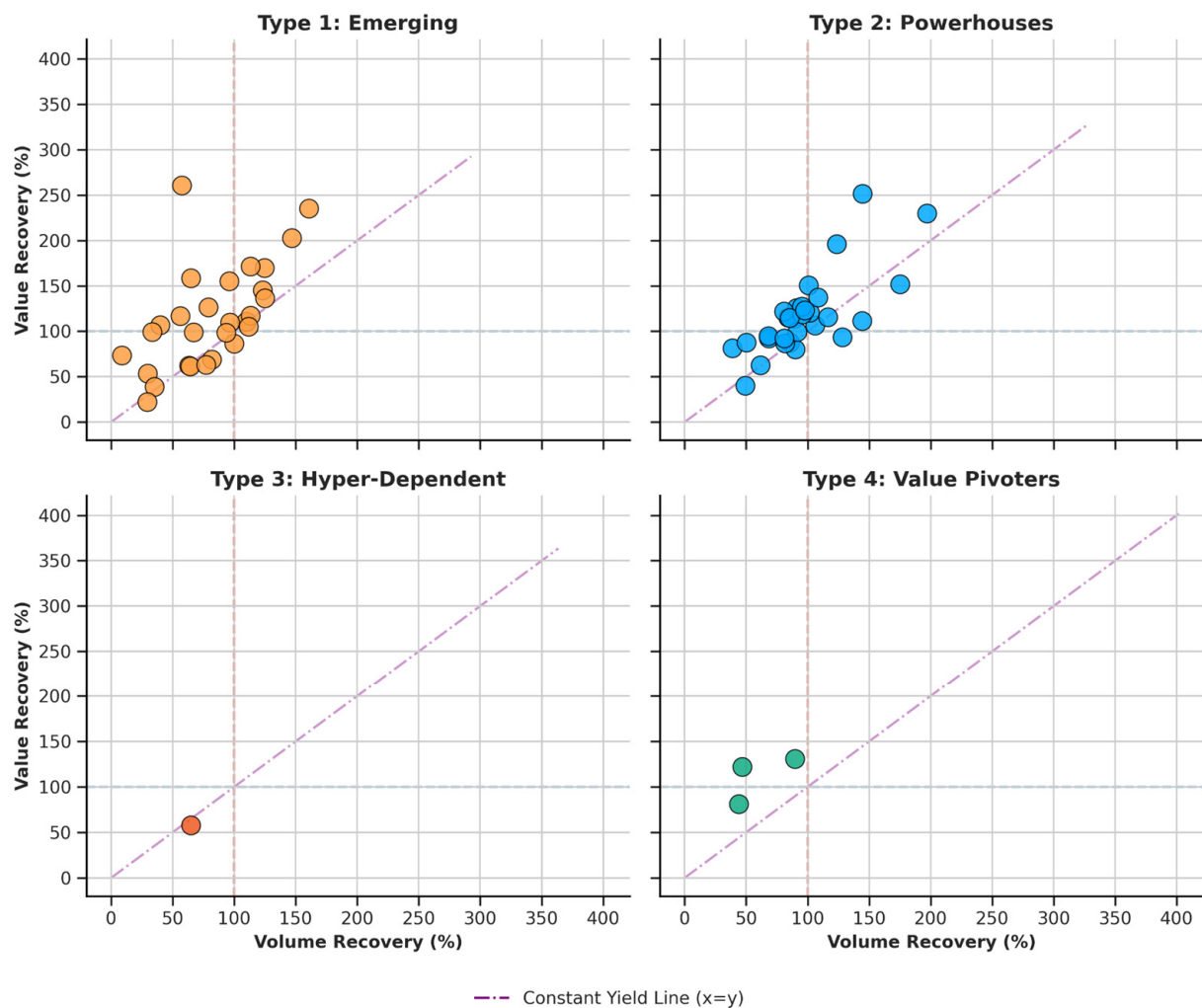


Figure 4. Intra-cluster heterogeneity in post-pandemic resilience. Facet grids display volume versus value recovery pathways for individual destinations within each archetype. Note: Figure 4 plots the recovery pathways for 62 out of the 80 classified destinations. The remaining 18 destinations, primarily developing economies, lack complete reporting for T1 receipts or arrivals and are therefore excluded from the recovery scatter plot. Values reflect nominal USD data; real recovery trajectories may differ due to the asymmetrical global inflationary shocks of the 2022–2023 period.

Similarly, the Emerging Markets (Type 1) bolstered their tourism value-added significantly, recording an average yield growth of 76.1%. Within this group, countries that proactively shifted their marketing and infrastructure focus toward high-net-worth segments emerged as the undisputed post-pandemic winners. Notable examples include Kuwait (+354.8% yield growth) and El Salvador (+235.3% value recovery), both of which achieved exponential financial gains despite not having fully recovered their pre-pandemic arrival volumes in some cases.

Conversely, states facing persistent domestic instability or severe infrastructure deficits failed to capture this value surge; for instance, Nigeria (22.3% value recovery) and Sri Lanka (39.0%) struggled to recover even half of their baseline economic value. This rapid escalation of yield within a subset of developing economies provides compelling evidence that the pandemic acted as a catalyst for a forceful transition toward market-driven premiumization in nominal terms. It indicates that economic resilience in the modern tourism landscape does not necessarily mandate a return to pre-pandemic levels of mass-volume tourism, but rather a strategic optimization of the nominal revenue generated per arrival. Crucially, while these parameters must be interpreted with caution as nominal gains that absorb

global supply-chain inflation rather than pure structural quality upgrades, they nonetheless demonstrate an enhanced liquidity-capture capacity across emerging destinations navigating post-crisis recovery.

It is therefore evident that while the established archetypes reliably capture structural baseline similarities (T0), the high dispersion in recovery rates (T1), as plotted in Figure 4, reflects the critical influence of localized, exogenous factors (e.g., health protocols, geopolitical shifts, and targeted policy interventions). A detailed breakdown of individual country performance metrics supporting these findings is provided in Table A5 in the Appendix B.

RQ1 core conclusion: Unsupervised machine learning separates global destinations into four structural profiles, proving that post-crisis financial recovery follows an intense K-shaped asymmetry where pre-pandemic capacities do not deterministically dictate resilience ($p > 0.05$).

4.2. RQ2: Environmental Accountability and Carbon Decoupling

4.2.1. Divergent Rebound Trajectories in Aviation Emissions

The environmental analysis (RQ2) involved a further refinement of the initial sample from $n = 80$ to $n = 41$ countries. A destination was retained only if it possessed comprehensive and synchronized reporting for international tourism receipts and aviation-related CO₂ emissions across the entire analysis timeframe, specifically ensuring data availability for the full T1 recovery period (2022–2024). This ensures that the environmental efficiency metrics reflect a consistent comparison between the pre-pandemic baseline (T0) and the actual recovery trajectory (T1).

Within this refined panel, Type 2 (Powerhouses, $n = 23$) and Type 1 (Emerging, $n = 17$) remained the dominant archetypes, while Type 4 (Value Pivoters) was represented solely by Tunisia, and Type 3 (Hyper-Dependent) was excluded due to data gaps. As illustrated in Figure 5a,b, and Table A5 in the Appendix A, the post-pandemic aviation emission trajectories diverge significantly. Within Type 2 (Powerhouses), several mature destinations successfully executed absolute decoupling, the optimal state where economic value grows while absolute emissions decline. Finland (FIN, DE: -6.87), Switzerland (CHE, DE: -2.46), Croatia (HRV, DE: -0.68), and Saudi Arabia (SAU, DE: -0.35) achieved the highest levels of absolute environmental efficiency. Other mature destinations, such as Italy (ITA, DE: 0.02) and Slovenia (SVN, DE: 0.39), exhibited relative decoupling ($0 < DE < 1$), achieving positive financial growth that outpaced their carbon growth, albeit with absolute emissions exceeding 2019 levels. In stark contrast, countries such as Austria (AUT, DE: 1.27), Belgium (BEL, DE: 3.43), and the Netherlands (NLD) fell into the Value Trap (Recoupling), as their post-pandemic resurgence in aviation carbon footprints significantly eclipsed their economic value recovery. Consequently, Type 1 (Emerging Markets) witnessed highly uneven carbon emission profiles and decoupling pathways. Leaders such as Oman (OMN, DE: -4.94), El Salvador (SLV, DE: -0.26), and Jordan (JOR, DE: -0.77) achieved strict absolute decoupling. Moldova (MDA, DE: 0.08) and Colombia (COL, DE: 0.24) achieved robust relative decoupling. Conversely, Luxembourg (LUX, DE: 9.96) registered severe environmental decline (Value Trap), with emissions surging by 250%.

Beyond economic metrics, the analysis suggests that institutional capacity acts as an invisible facilitator, though not a guarantor, of this transition. Top-performing “Absolute Decoupling” leaders maintain a solid Human Capital Index (mean HCI = 0.636), comparable to those in the “Value Trap” (mean HCI = 0.655). This minimal difference reinforces the finding that environmental success is less about baseline wealth and more about destination-specific strategic pivots.

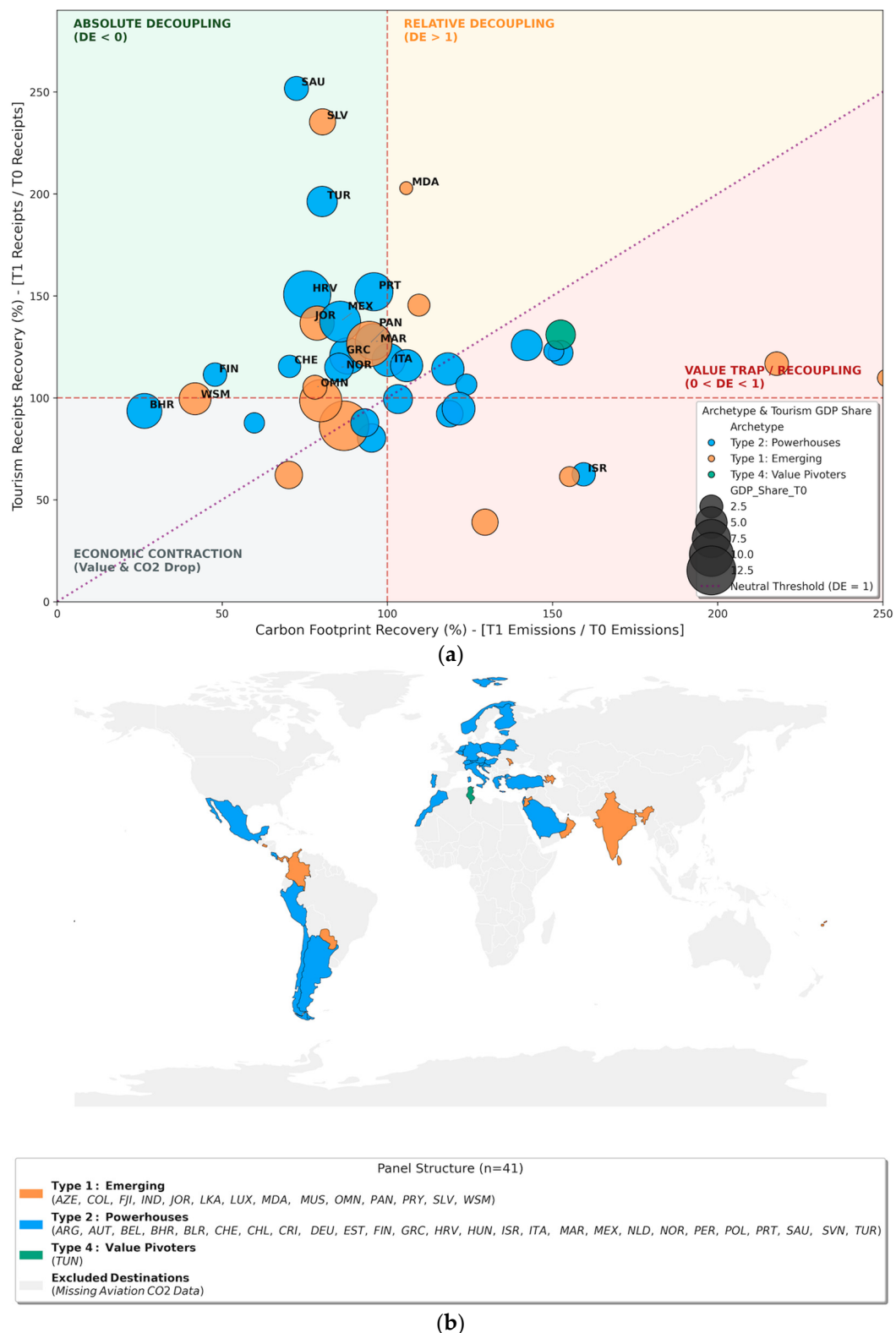


Figure 5. (a). Aviation emissions rebound and decoupling quadrant map. Bubble size corresponds to the pre-pandemic tourism GDP share, highlighting the intersection between economic vulnerability (dependency) and carbon-intensive recovery pathways. (b). Geographic distribution of the environmental panel. Colors represent the structural tourism archetypes (Types 1, 2, and 4), identifying the 41 synchronized destinations included in the carbon decoupling analysis. Note: The analysis focuses on a synchronized sub-sample ($n = 41$) with complete environmental and economic data for T1. In Figure 5a, data labels are selectively applied to absolute top/bottom decoupling performers and high-dependence outliers to preserve visual clarity.

4.2.2. Non-Parametric Variance and Policy Decoupling Elasticities

To statistically validate whether pre-pandemic structural archetypes inherently dictated these post-pandemic environmental trajectories, a Kruskal–Wallis H-test was conducted on the decoupling elasticity scores. The results ($H = 2.183$, $p = 0.336$) revealed no statistically significant variance between the structural clusters. This extends the intra-cluster heterogeneity observed in economic resilience (RQ1) directly into the environmental domain. It empirically confirms that a destination's pre-pandemic macroeconomic 'DNA' did not deterministically constrain its ecological transition. Instead, states of absolute decoupling and Value Traps emerged organically across all archetypes, underscoring that environmental resilience is largely driven by localized, agile policy interventions, rather than static macroeconomic baselines.

The analysis leads to the conclusion that the environmental performance of a destination is not predetermined by the archetype to which it belongs. The relationship between economic recovery and carbon footprint is not linear, but is shaped by the strategic choices of national tourism authorities. The fact that top performances in decoupling are observed in both mature economies (e.g., Switzerland, Turkey) and emerging ones (e.g., El Salvador) demonstrates that the sustainability of the recovery is the result of targeted policy and not a passive result of economic power. Specifically, the destinations that managed to 'break' the link between revenues and pollutants are those that moved from a model of mass tourism to a model of optimizing the value-added performance per visitor. For instance, as detailed in Table A4, destinations like Croatia (value recovery: 150.6%, CO₂ recovery: 75.7%) and El Salvador (value recovery: 235.3%, CO₂ recovery: 80.4%) successfully generated exponential revenue growth while simultaneously maintaining their aviation emissions strictly below pre-pandemic levels.

RQ2 core conclusion: Cross-border eco-efficiency is highly non-linear ($H = 2.183$, $p = 0.336$), demonstrating that absolute decoupling (e.g., Saudi Arabia, El Salvador) or carbon-intensive value traps occur across all archetypes based on localized policy shifts rather than baseline wealth.

4.3. RQ3: Recovery Accelerators and the Role of Digital Attractiveness

4.3.1. Associative Power and Coefficients of the OLS Architecture

After identifying the structural archetypes (RQ1) and their environmental efficiency (RQ2), the empirical analysis in RQ3 focuses on the exogenous predictors associated with recovery velocity. The central hypothesis examines whether air connectivity, expressed through the strategic centrality of the aviation network (PageRank), remains the dominant driver of resilience, or whether the digital attractiveness of a destination acts as a stronger accelerator. To quantify these effects, an Ordinary Least Squares (OLS) regression model was applied to a subset of $n = 18$ global destinations (Table 3), capturing approximately 44% of global digital nomad activity. As detailed in the methodology, this approach acknowledges the potential endogeneity between digital attractiveness and high-yield recovery. Rather than asserting strict unidirectional causality, the study treats the Digital Nomad Market Share as a macro-proxy for a destination's "soft" institutional capacity, remote-work readiness, and overarching lifestyle brand equity.

The analysis of Table 3 reveals that 83% of the top digital destinations belong to Type 2 (Powerhouses), confirming that mature destinations with high human capital and stable infrastructure maintain a strategic advantage in attracting digital nomads. However, the presence of Colombia, India, and Indonesia (Type 1) suggests that emerging markets are leveraging their digital reputation as a tool to overcome structural lags.

Table 3. Structural profiling of the elite digital destinations (n = 18).

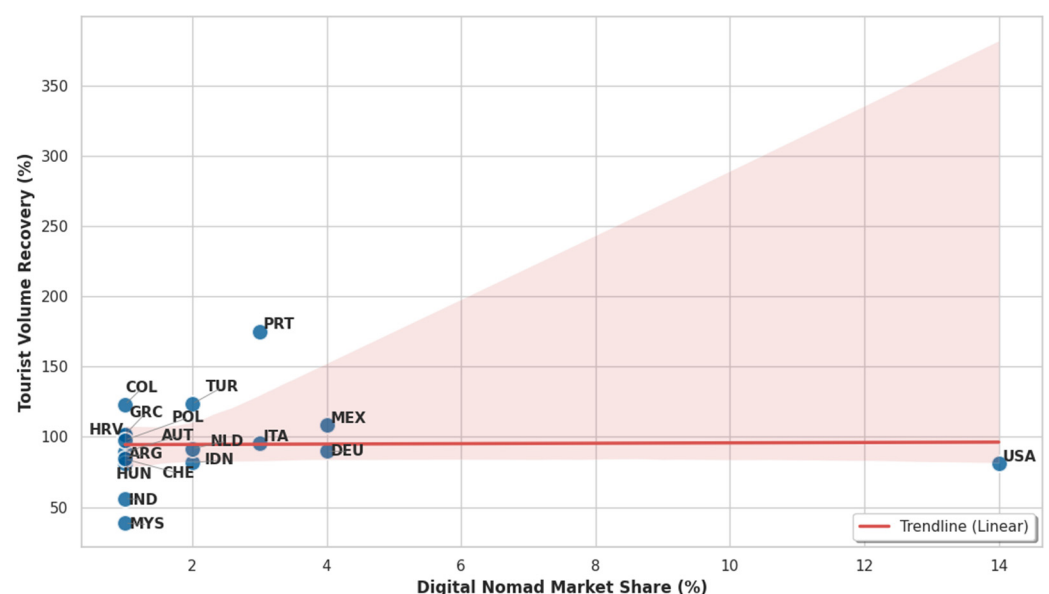
Structural Archetype (from RQ1)	Included Destinations in the Elite Cohort	Count
Type 1: Emerging Markets	Colombia, India, Indonesia	3
Type 2: Powerhouses	Argentina, Austria, Croatia, Germany, Greece, Hungary, Italy, Malaysia, Mexico, Netherlands, Poland, Portugal, Switzerland, Turkey, United States	15
Type 3: Yield Leaders	-	0
Type 4: Value Pivoters	-	0
Total		18

The inclusion of the global Digital Nomad Market Share (%) as a proxy for digital reputation yielded substantial explanatory power for an exploratory model ($R^2 = 0.407$, as detailed in Table 4). Digital attractiveness emerged as the strongest and statistically significant positive accelerator ($\beta = 55.5880$, $p = 0.019$). The relative magnitudes of these predictors and their respective 95% confidence intervals are visually summarized in Figure A1 in the Appendix B. As visualized in the scatter plot (Figure 6), there is a clear positive linear association: destinations with a strong global digital brand and remote-work readiness achieved significantly faster recovery, overshadowing the isolated effects of pre-pandemic market size or structural archetypes (both of which were non-significant).

Table 4. OLS regression results: accelerators of tourist volume recovery (RQ3).

Predictor Variables	Coefficient (β)	Std. Error	t-Statistic	p-Value
(Constant)	329.4361	128.300	2.568	0.023 *
Aviation Connectivity (Z_PageRank)	−46.4803	19.839	−2.343	0.036 *
Digital Attractiveness (Z_Nomads)	55.5880	20.840	2.667	0.019 *
Control Variables				
Market Size Baseline (Log_Passengers)	−27.8175	15.722	−1.769	0.100
Archetype Baseline (Type 2: Powerhouses)	−25.0744	21.811	−1.150	0.271

Notes: Dependent variable: tourist volume recovery (%). n = 18 globally ranked digital nomad destinations. $R^2 = 0.407$, Adjusted $R^2 = 0.224$, F-statistic = 2.229 ($p = 0.122$). Significance level: * $p < 0.05$. Statistical diagnostics confirm normal distribution of residuals (Shapiro–Wilk $p = 0.155$) and homoscedasticity (Breusch–Pagan $p = 0.621$).

**Figure 6.** Scatter plot of digital attractiveness (nomad share) vs. tourist volume recovery.

4.3.2. Econometric Friction, Multicollinearity, and the Accessibility Nexus

Conversely, physical aviation infrastructure (PageRank centrality) yielded a negative coefficient ($\beta = -46.48$, $p = 0.036$). However, this specific directional shift is interpreted with statistical caution and cannot be translated as a literal structural penalty on physical connectivity. Diagnostic testing revealed severe multicollinearity between the standardized PageRank score and the Digital Nomad Market Share, with Variance Inflation Factors substantially exceeding the conventional warning thresholds ($VIF > 10$). This econometric friction reflects an underlying structural reality where global aviation mega-hubs inherently function as primary nodes for remote-work ecosystems. Because the individual coefficient estimates become unstable under such intense variance overlap, the OLS framework cannot reliably isolate or separate their independent effects. Consequently, the negative coefficient is treated as a statistic with severe multicollinearity rather than an isolated material friction, confirming that physical route networks and digital attractiveness must be interpreted substantively as a singular, unified destination accessibility nexus.

A critical theoretical nuance, warranting future empirical testing at the micro level, concerns the conceptual association between digital nomads and destination “premiumization”. The tourism literature often equates premiumization strictly with luxury hospitality and high daily expenditure. However, the study hypothesized that the global digital nomad community frequently operates on the principle of “geo-arbitrage”, leveraging high-income remote salaries against lower local living costs in emerging destinations. Under this conceptual framework, premiumization is redefined as cumulative yield optimization. While remote workers may exhibit lower daily spending compared to short-haul leisure tourists, their exceptionally prolonged length of stay, integration into local non-tourist supply chains, and reduced frequency of international flights theoretically result in a structurally superior economic-to-environmental ratio.

In response to RQ3, the empirical evidence underscores that digital maturity acts as a highly potent accelerator of recovery for the global digital vanguard. A destination’s ability to build an attractive digital ecosystem and appeal to high-yielding, long-stay traveler segments serves as a robust predictor of resilience. While physical connectivity remains the foundational baseline, for global “digital pioneers”, soft infrastructure and virtual accessibility have emerged as transformative equalizers in the post-pandemic era.

RQ3 core conclusion: For the digital vanguard, soft destination branding proxied by digital nomad market share is a significantly stronger positive accelerator of volume recovery ($\beta = 55.59$, $p = 0.019$) than traditional physical route centrality.

4.4. RQ4: Strategic Synthesis and Policy Simulation: The Post-COVID Decision Matrix Strategic Decision Matrix Geometry and Actionable Quadrants

The empirical analysis is completed through the construction of the Strategic Decision Matrix (Figure 7), which performs the overall theoretical and computational synthesis of the findings that emerged from the study of structural archetypes (RQ1), environmental efficiency (RQ2), and dynamic recovery accelerators (RQ3). By placing the comprehensive panel of 41 destinations in a two-dimensional field, where the horizontal axis captures the economic resilience (Val_Rec_pct) and the vertical axis represents the environmental decoupling elasticity (Tapio Standard DE), a dynamic roadmap emerges for tourism policy-making. The precise strategic classification of all evaluated destinations into their respective matrix quadrants is summarized in Table A5 in the Appendix B. For the exact numerical coordinates of each destination (value recovery and DE) that dictate their placement in this matrix, readers are directed to Table A4 (RQ2). The market share of digital nomads is incorporated as the bubble size exclusively for the $n = 18$ sample identified in RQ3, empirically illustrating the role of digital attractiveness.

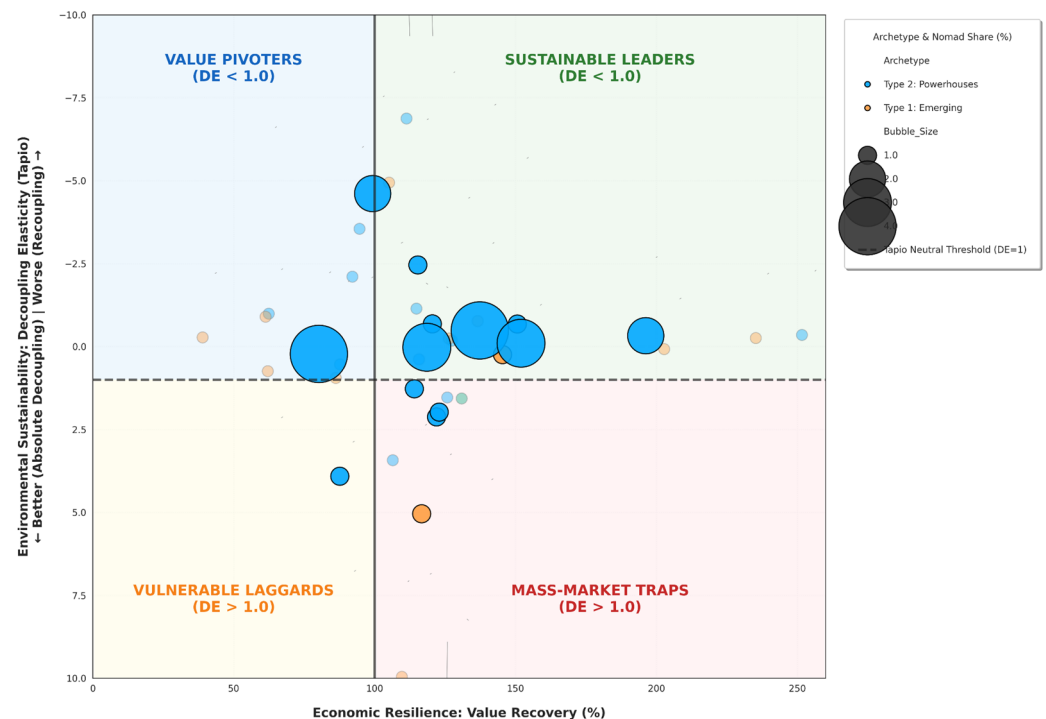


Figure 7. Strategic decision matrix for sustainable tourism transitions ($n = 41$). Notes: The policy matrix maps the complete synchronized environmental sub-sample ($n = 41$) to enable a system-wide comparative analysis. Crucially, the quantitative volume scaling of the digital nomad bubble sizes reflects empirical market share data exclusively for the elite digital vanguard cohort ($n = 18$). Conversely, destinations lacking specialized digital nomad index tracking are plotted using a standardized baseline placeholder value for the digital vector, as detailed in Footnote 1 below. (The 23 destinations plotted using a standardized baseline placeholder value comprise Finland, Oman, Norway, Jordan, Saudi Arabia, El Salvador, Panama, Morocco, Moldova, Slovenia, Costa Rica, Tunisia, Belgium, Luxembourg, Estonia, Chile, Israel, Paraguay, Sri Lanka, Peru, Azerbaijan, Fiji, Mauritius, Bahrain, Samoa, and Belarus. This operational adjustment preserves their macro-environmental positioning on the decoupling axis while transparently bounding their digital attractiveness classification to prevent analytical overclaiming).

The Sustainable Leaders (High Resilience/High Decoupling, $DE < 1$) quadrant represents the optimal development paradigm of the modern tourism economy. Encompassing 14 destinations, comprising four Type 1 (Emerging) and ten Type 2 (Powerhouses) archetypes, this zone demonstrates that robust income recovery can successfully coexist with high environmental efficiency. At the vanguard of this quadrant, destinations such as Saudi Arabia (SAU, $DE = -0.35$) and El Salvador (SLV, $DE = -0.26$) lead the global ranking, showcasing exceptional resilience combined with a radical absolute decoupling from the carbon footprint of international flights.

A deeper intra-quadrant analysis reveals distinct, archetype-specific pathways to sustainable leadership. The predominance of Type 2 (Powerhouses), which includes mature markets like Greece, Croatia, Portugal, Mexico, and Switzerland, proves that historically high-volume destinations can successfully reverse their carbon-intensive trajectories. For these markets, the sustainable transition is heavily mediated by digital attractiveness. The strong presence of destinations with expanded digital nomad market shares validates the theoretical hypothesis of RQ3 that mature destinations are leveraging “soft” digital infrastructure and remote-work readiness to attract high-yield, longer-stay travelers, thereby decoupling revenue from aviation intensity. Conversely, the presence of Type 1 (Emerging) destinations, such as Jordan, Oman, and Panama, highlights a phenomenon of structural

leapfrogging. Rather than following the traditional, carbon-heavy growth stages, these developing markets are capturing high-value-added segments early in their recovery cycle.

In contrast, the Mass-Market Traps (High Resilience/Recoupling, $DE > 1$) quadrant highlights the structural risks of an Expansive Value Trap, where the perilous focus on arrival volume overrides ecological sustainability. Comprising eight destinations (5 Type 2, 2 Type 1, and 1 Type 4), this zone features countries that achieved full recovery of their tourism inflows ($Val_Rec_pct > 100\%$), yet remain structurally trapped in a carbon-intensive model.

An intra-quadrant examination of the dominant Type 2 (Powerhouses) in this group, namely Austria (AUT, $DE: 1.27$), Belgium (BEL, $DE: 3.43$), and Poland (POL, $DE: 1.98$), documents a case of structural path dependency. Relying on their integration into short-haul aviation networks, their rapid financial recovery masks deep environmental vulnerabilities. Furthermore, the presence of Tunisia (TUN, $DE: 1.57$) highlights a critical disconnect between this specific destination's individual structural potential and its actual crisis-management tactics. Although Tunisia is macroeconomically classified as a Type 4 "Value Pivoter", an archetype theoretically aligned with high-yield, lower-volume tourism, its severe decoupling elasticity indicates a disproportionate surge in emissions relative to revenue growth. The urgent need for immediate post-pandemic liquidity forced a temporary regression into carbon-intensive, mass-market tourism. While this single-observation outcome ($n = 1$) cannot be statistically extrapolated to characterize the entire Type 4 cohort, it demonstrates on an individual level that being inherently structured for quality-driven tourism does not automatically guarantee an eco-efficient recovery without strict environmental policy enforcement.

The Value Pivoters (Low Resilience/High Decoupling, $DE < 1$) quadrant comprises 4 destinations that have successfully operationalized a 'Value-over-Volume' strategy. These destinations are sacrificing the speed of absolute recovery to secure substantially higher ecological efficiency. Type 2 regional powerhouses in this zone, specifically Italy (ITA, $DE: 0.02$) and Slovenia (SVN, $DE: 0.39$), are exhibiting a calculated lag in aggregate financial recovery as they actively shed low-yield mass segments in favor of yield optimization (relative decoupling). Conversely, Type 1 destinations in this quadrant, such as Moldova and Colombia, utilized travel disruptions to execute a strategic reset. For policymakers in this zone, the strategic priority shifts to revenue acceleration via "soft infrastructure leapfrogging," enhancing their digital reputation to migrate horizontally into the Sustainable Leadership quadrant.

Finally, the Vulnerable Laggards (Low Resilience/Recoupling, $DE > 1$ or anomalous) quadrant maps out 14 destinations facing a dual structural crisis: economic contraction coupled with a severe environmental burden (Collapse Value Trap). An intra-quadrant examination reveals differing root causes for this vulnerability. For mature Type 2 (Powerhouses), most notably Germany (DEU) and the Netherlands (NLD), this placement highlights a conceptual nuance. Their lag is not indicative of economic vulnerability, but rather structural inertia. Relying heavily on legacy aviation infrastructure, these nations maintained high baseline aviation emissions to keep transit networks operational, yet suffered disproportionately from the delayed resurgence of the corporate and business travel segments. Conversely, Type 1 (Emerging) destinations in this zone, such as Sri Lanka, Peru, and Fiji, highlight extreme susceptibility to exogenous macroeconomic shocks, where the delayed return of international tourists heavily skewed their decoupling metrics. To escape this zone, policymaking demands radical structural restructuring. Based on the RQ3 regression results, digital attractiveness could be utilized as a primary strategic lever to bypass traditional, volume-based growth stages. By aggressively investing in soft digital

infrastructure and remote-work readiness, these laggards can transition toward longer-stay, high-yield segments, breaking the vicious cycle of low eco-efficiency.

RQ4 core conclusion: The 2×2 matrix successfully operationalizes interdisciplinary metrics into four clear, actionable quadrants, demonstrating that sustainable leadership (Value $\geq 100\%$, DE < 1) is achievable for both mature and emerging markets via value-driven premiumization.

5. Conclusions

The study achieves a theoretical and empirical synthesis, bridging the existing gap between the fields of economic geography, digitalization and ecological economics in the context of tourism research. Through a multidimensional methodological framework, the paper analyzes the post-pandemic pathways of destinations, transforming the quantitative findings into a policy guide. The main conclusions are systematically structured around four central research questions (RQs).

5.1. Limitations and Methodological Boundaries

Despite the methodological and empirical contributions of this study, certain limitations must be acknowledged. First, the Environmental Decoupling Index focuses exclusively on aviation-induced CO₂. While aviation is the most carbon-intensive Scope 3 emission source in tourism, this parameterization introduces inherent structural biases. It grants a ‘land-border advantage’ to continental destinations that can substitute flights with rail or road transport, while imposing a severe “long-haul penalty” on geographically isolated Small Island Developing States (SIDS), which possess no alternatives to air connectivity. Consequently, the local ecological footprint of destinations (e.g., energy consumption in hotel infrastructure, solid waste management) is not captured. Additionally, the strict requirement for complete aviation CO₂ reporting reduced the environmental analysis panel to 41 destinations, introducing a geographical data bias in which developing nations (particularly the Type 4 archetype in Africa) were severely underrepresented.

Secondly, the value recovery (%) metric relies on nominal US Dollars, which inherently absorb the asymmetrical global inflationary shocks of the 2022–2023 period. Therefore, some yield premiumization may reflect inflationary pricing rather than pure structural upgrading. Thirdly, holding the Human Capital Index (HCI) static at 2020 levels represents a distinct analytical limitation, as it inherently assumes a constant cross-country rank-order stability in macro-demographic endowments throughout the 2020–2024 tracking window. While this parameterization is methodologically justified by the high structural inertia and severe path dependency characteristics of national demographic stocks, it inevitably overlooks the highly asymmetrical disruptions that the pandemic inflicted on human capital development across different territories. Specifically, localized strains on national healthcare systems, variable periods of country-level schooling closures, and post-crisis labor emigration patterns differed enormously worldwide, potentially altering fine-grained human development trajectories. Consequently, broad country-level macroeconomic indicators may mask these temporary structural shifts, alongside acute sector-specific micro-shocks, such as the severe hospitality labor deficits (‘Great Resignation’), and emerging digital skills gaps that are not captured within traditional baseline demographic aggregates [48,49]. Finally, regarding digital attractiveness, the Statista dataset exhibits inherent sample bias, heavily over-representing Western-centric (primarily U.S.) destination preferences. Furthermore, the 2022–2024 recovery window was characterized by the transient phenomenon of “revenge travel”, which may be normalized in the coming years.

5.2. Future Research Directions

Cognizant of the aforementioned methodological boundaries and data constraints, the empirical insights are organized around the four central research questions (RQs). Destination Archetypes and Resilience (RQ1): The empirical analysis documents that post-pandemic tourism recovery is not homogeneous but follows a divergent K-shaped trajectory. Through the application of K-Means clustering, four distinct structural destination archetypes were identified. The results demonstrate that while the pre-pandemic “DNA” of a destination, defined by its economic dependence, human capital quality, and productive efficiency (yield), establishes its baseline capacity, it does not deterministically dictate its ultimate recovery. Instead, resilience proved to be highly elastic, driven by localized exogenous factors and agile policy pivots.

Environmental Efficiency and Decoupling (RQ2): The introduction of the Environmental Decoupling Index revealed a critical structural asymmetry. Rapid financial recovery often masks exponential atmospheric carbon loading. While macro-level environmental degradation fundamentally implies the systemic deterioration of all surrounding biotic and abiotic parameters, including water, soil, and biological resource depletion, as established by [50], the specific empirical focus of this international transit module highlights the localized atmospheric strain of aviation emissions. This finding debunks the prevailing myth that increasing tourism revenues automatically leads to “green” growth [51], highlighting the risk of “Mass-Market Traps”, where the environmental burden of international air transport grows faster than the economic value generated [39,40]. This interpretation is consistent with recent Tapio-type decoupling analyses, which show that tourism-based income growth does not automatically imply a reduction in emissions [52]. Although tourism is frequently framed as a vehicle for green growth in policy discourse, empirical evidence indicates that aviation-related emissions remain the dominant driver of carbon pollution, undermining the assumption that revenue expansion is inherently sustainable [39].

Digital Leverage vs. Physical Infrastructure (RQ3): The results of the regression models highlighted a paradigm shift in recovery dynamics. The digital attractiveness of a destination, expressed through the global Digital Nomad Market Share, emerged as a statistically stronger accelerator of tourist volume recovery compared to traditional, physical air connectivity (PageRank centrality). This underlines the strategic superiority of “soft infrastructures” and lifestyle appeal in the modern tourism economy. This fact underlines the strategic superiority of “soft infrastructures” and lifestyle appeal in the modern tourism economy [53,54], where lifestyle-driven segments such as digital nomads respond more strongly to branded, experience-rich imagery and digital connectivity than to pure route-level physical access [54,55].

Strategic Transition Roadmaps (RQ4): The construction of the Strategic Decision Matrix transformed the theoretical analysis into an applicable policy simulation. It is found that “Sustainable Leadership” is not an exclusive privilege of economically developed countries, but is feasible for both mature and emerging markets. A prerequisite for this transition is the abandonment of models based solely on the volume of arrivals and the adoption of premiumization and leapfrogging strategies [48,56].

5.3. Potential Applications and Operational Value of the Model

The developed multi-stage computational matrix serves as an actionable decision-support tool for sustainable tourism governance and regional policy simulation. Destination Management Organizations (DMOs) can directly deploy this scale-invariant framework to benchmark local transition pathways, allowing them to diagnose hidden carbon recouping risks before launching high-volume tourism expansions. Furthermore, international funding bodies and national planning agencies can utilize the objective positioning centroids to

channel strategic infrastructure investments, rewarding absolute carbon decoupling with premium branding credentials while systematically deploying digital upskilling resources to vulnerable laggard archetypes.

5.4. Empirical Conclusions and Policy Implications

Based on these limitations, future institutional efforts must prioritize comprehensive, standardized carbon tracking for developing destinations. Future scientific research should integrate local sustainability indicators (e.g., circular economy metrics) and cruise-ship emissions to recalibrate the overall ecological footprint. Additionally, future studies should employ PPP-adjusted (Purchasing Power Parity) real values to isolate pure economic growth. Methodologically, it is proposed to iterate the Strategic Decision Matrix with a horizon of 2030 to dynamically map the movement of countries across quadrants and evaluate the long-term effectiveness of implemented green policies. Finally, researchers can utilize advanced supervised learning algorithms (e.g., Random Forests, Gradient Boosting) to predict the probability of a destination slipping into the Vulnerable Laggards category, functioning as an early warning system for sustainable destination management.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study. Detailed information regarding the specific data sources, including UN Tourism, the World Bank, OECD, Our World in Data (OWID), and Statista, is comprehensively documented in the appendix of this article. The final harmonized datasets and computational outputs generated during the current study are available from the corresponding author upon reasonable request.

Acknowledgments: During the preparation of this manuscript, the author used Google Gemini 3.1 Pro for language editing. The author has reviewed and edited the output and takes full responsibility for the content of this publication.

Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CO ₂	Carbon Dioxide
DE	Decoupling Elasticity (Decoupling Index)
GDP	Gross Domestic Product
HCI	Human Capital Index
INSTO	International Network of Sustainable Tourism Observatories
LOS	Length of Stay
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
OWID	Our World in Data
PPP	Purchasing Power Parity
RQ	Research Question
SIDS	Small Island Developing States
UNEP	United Nations Environment Programme
USD	United States Dollar
VIF	Variance Inflation Factor
WTTC	World Travel & Tourism Council

Appendix A. Master Data Dictionary and Methodological Specifications

Table A1. Master data dictionary, variable derivations, and functional roles across all research phases (RQ1–RQ4).

No.	Variable	Category/Role	Source/Formula	Sample (N)	Timeframe	Functional Rationale
Phase 1: Structural Archetypes & Resilience (RQ1)						
1	International Tourism Receipts	Primary (Clustering)	UN Tourism/OWID	112	2015–2024	Numerator for calculating the generated Value Added (Yield).
2	International Arrivals	Primary (Clustering)	UN Tourism/OWID	112	2015–2024	Reflects the volume and specific weight of the destination (Market Scale).
3	Tourism GDP Share (%)	Primary (Clustering)	UN Tourism/OWID	112	2015–2024	Indicator of macroeconomic dependence and structural vulnerability.
4	Human Capital Index (HCI)	Primary (Clustering)	World Bank	174	2020	Assesses service quality capacity. Used as a static 2020 “stock” metric.
5	Average Length of Stay	Secondary (Profiling)	UN Tourism/OWID	112	2015–2019	Differentiates between long-term destinations and high-velocity transit markets.
6	GDP per Capita	Secondary (Profiling)	World Bank	195	2019	Verifies the pre-crisis economic development level of the generated clusters.
7	Tourism Employment	Secondary (Profiling)	UN Tourism	38	2022–2023	Empirically validates the post-pandemic ‘Great Resignation’ effect.
Phase 2: Environmental Accountability & Eco-Efficiency (RQ2)						
9	Aviation CO ₂ Emissions	Primary Data	OECD/OWID	212	2013–2024	Base metric for environmental cost (tonnes of CO ₂ per capita).
10	Total Absolute CO ₂	Engineered Feature	Calculated: [CO ₂ per capita] × [Population]	41	2019 & 2022–2024	Derived total carbon mass (metric tons) per destination.
11	Carbon Footprint Recov. (%)	Engineered Feature	Calculated: $(CO_{2_T1}/CO_{2_T0}) \times 100$	41	2015–2024	Evaluates the resurgence of absolute aviation emissions.
12	Tourism Eco-Efficiency	Engineered Feature	Calculated: [Receipts]/[Total CO ₂]	41	2015–2024	Measures the economic value (USD) generated per unit of carbon.
13	Decoupling Index (DE)	Engineered Feature	Calculated: $\ln(CO_{2_T1}/CO_{2_T0})/\ln(Value_T1/Value_T0)$	41	2019 & 2022–2024	Primary elasticity metric measuring the relationship between financial and carbon growth.
14	Renewable Energy Share	Secondary (Validation)	World Bank/OWID	195	2000–2023	Contextual profiling of a destination’s broader green transition.
Phase 3: Recovery Accelerators (RQ3)						
15	Tourist Volume Recov. (%)	Dependent Variable	Derived from RQ1	80	2015–2019 vs. 2022–2024	The primary metric of post-pandemic tourist volume resurgence.
16	Aviation PageRank Score	Predictor (Physical)	Calculated via NetworkX (OAG/IATA data)	195	2023	Evaluates global connectivity network centrality. High values indicate strategic hubs.
17	Digital Nomad Share (%)	Predictor (Digital)	[47]	30	2025	Proxy for digital infrastructure, remote-work readiness, and modern brand equity.
18	Air Passengers (Log ₁₀)	Control (Size)	World Bank	195	2019	Controls for the pre-pandemic market scale and baseline aviation capacity.
19	Archetype Dummies	Control (Structure)	Inherited from RQ1	80	2015–2019	Controls for inherent structural differences (e.g., Type 2 Powerhouses).
Phase 4: Strategic Synthesis & Decision Matrix (RQ4)						
21	Economic Value Recov. (%)	Synthesis (X-Axis)	Derived from RQ1	41	2015–2019 vs. 2022–2024	Primary measure of economic resurgence (Resilience dimension).

Table A1. *Cont.*

No.	Variable	Category/Role	Source/Formula	Sample (N)	Timeframe	Functional Rationale
22	Decoupling Index (DE)	Synthesis (Y-Axis)	Derived from RQ2	41	2015–2019 vs. 2022–2024	Primary measure of eco-efficiency (Sustainability dimension).
23	Digital Nomad Share (%)	Strategic Lever (Z)	[47]	18	2025	Evaluates the “Digital Pull” acting as a facilitator for quadrant migration.
24	Value-over-Volume Gap	Synthesis Metric	Calculated: [Value_Rec %] – [Volume_Rec %]	41	2015–2019 vs. 2022–2024	Identifies the intensity of the destination’s shift toward premiumization/yield.

Appendix B. Supplementary Empirical Results and Statistical Diagnostics

Table A2. Correlation matrix and variance inflation factors (VIF) (RQ1).

	GDP_Share_T0	HCI_2020	Log_Arrivals_T0	Log_Yield_T0	VIF
GDP_Share_T0	1.000	0.176	0.117	0.142	1.04
HCI_2020	0.176	1.000	0.541	0.324	1.68
Log_Arrivals_T0	0.117	0.541	1.000	−0.002	1.49
Log_Yield_T0	0.142	0.324	−0.002	1.000	1.19

Table A3. Full list of classified countries by archetype (RQ1).

Country	ISO	Archetype	Volume Recovery (%)	Value Recovery (%)	Yield Growth (%)
Antigua and Barbuda	ATG	Type 1: Emerging	109.7	110.7	0.9
Azerbaijan	AZE	Type 1: Emerging	63.2	62.1	−1.7
Bangladesh	BGD	Type 1: Emerging	N/A	150.4	N/A
Bhutan	BTN	Type 1: Emerging	8.6	73.7	753.1
Colombia	COL	Type 1: Emerging	123.0	145.4	18.2
Costa Rica	CRI	Type 1: Emerging	90.9	125.8	38.3
Egypt	EGY	Type 1: Emerging	124.7	169.7	36.1
El Salvador	SLV	Type 1: Emerging	160.7	235.3	46.4
Ethiopia	ETH	Type 1: Emerging	64.7	158.6	145.1
Fiji	FJI	Type 1: Emerging	100.1	86.2	−13.9
India	IND	Type 1: Emerging	56.1	116.7	107.9
Indonesia	IDN	Type 1: Emerging	81.6	87.0	6.6
Jordan	JOR	Type 1: Emerging	124.9	136.6	9.4
Kenya	KEN	Type 1: Emerging	N/A	110.3	N/A
Kiribati	KIR	Type 1: Emerging	29.6	53.6	81.2
Kuwait	KWT	Type 1: Emerging	57.3	260.6	354.8
Kyrgyzstan	KGZ	Type 1: Emerging	95.9	155.1	61.7
Lebanon	LBN	Type 1: Emerging	81.8	68.8	−15.8
Luxembourg	LUX	Type 1: Emerging	81.8	109.7	13.7
Marshall Islands	MHL	Type 1: Emerging	N/A	N/A	N/A
Mauritius	MUS	Type 1: Emerging	93.5	98.5	5.4
Moldova	MDA	Type 1: Emerging	146.8	202.8	38.1
Mongolia	MNG	Type 1: Emerging	113.2	117.2	3.5
Morocco	MAR	Type 1: Emerging	95.2	127.4	33.8
Nepal	NPL	Type 1: Emerging	66.8	99.1	48.4
Nigeria	NGA	Type 1: Emerging	29.4	22.3	−24.1
North Macedonia	MKD	Type 1: Emerging	113.3	171.6	51.5
Oman	OMN	Type 1: Emerging	111.7	105.1	−5.9
Palau	PLW	Type 1: Emerging	N/A	9.6	N/A
Panama	PAN	Type 1: Emerging	79.0	126.4	59.9
Paraguay	PRY	Type 1: Emerging	64.2	61.3	−4.5
Peru	PER	Type 1: Emerging	50.2	87.7	74.8
Philippines	PHL	Type 1: Emerging	39.8	106.8	168.6
Samoa	WSM	Type 1: Emerging	33.2	99.5	199.7
South Africa	ZAF	Type 1: Emerging	77.1	63.2	−18.0

Table A3. Cont.

Country	ISO	Archetype	Volume Recovery (%)	Value Recovery (%)	Yield Growth (%)
Sri Lanka	LKA	Type 1: Emerging	35.2	39.0	10.6
Uganda	UGA	Type 1: Emerging	N/A	99.5	N/A
Uruguay	URY	Type 1: Emerging	N/A	83.4	N/A
Albania	ALB	Type 2: Powerhouses	197.0	229.8	16.7
Argentina	ARG	Type 2: Powerhouses	85.8	87.7	2.2
Austria	AUT	Type 2: Powerhouses	89.2	114.1	28.0
Bahrain	BHR	Type 2: Powerhouses	128.3	93.5	−27.1
Belarus	BLR	Type 2: Powerhouses	80.7	N/A	N/A
Belgium	BEL	Type 2: Powerhouses	106.0	106.5	0.5
Chile	CHL	Type 2: Powerhouses	68.4	92.1	34.7
Croatia	HRV	Type 2: Powerhouses	100.7	150.6	49.6
Czechia	CZE	Type 2: Powerhouses	N/A	107.9	N/A
Estonia	EST	Type 2: Powerhouses	68.1	94.6	38.9
Finland	FIN	Type 2: Powerhouses	144.4	111.3	−22.9
France	FRA	Type 2: Powerhouses		113.9	
Germany	DEU	Type 2: Powerhouses	89.9	80.2	−10.7
Greece	GRC	Type 2: Powerhouses	101.5	120.5	18.7
Hong Kong	HKG	Type 2: Powerhouses	49.3	40.0	−18.9
Hungary	HUN	Type 2: Powerhouses	80.9	122.0	50.9
Ireland	IRL	Type 2: Powerhouses	N/A	118.5	N/A
Israel	ISR	Type 2: Powerhouses	61.6	62.4	1.4
Italy	ITA	Type 2: Powerhouses	95.5	118.5	24.0
Malaysia	MYS	Type 2: Powerhouses	38.6	81.4	110.7
Mexico	MEX	Type 2: Powerhouses	108.3	137.3	26.8
Netherlands	NLD	Type 2: Powerhouses	91.6	99.3	8.4
Norway	NOR	Type 2: Powerhouses	85.4	114.8	34.4
Poland	POL	Type 2: Powerhouses	97.7	122.9	25.8
Portugal	PRT	Type 2: Powerhouses	175.1	152.0	−13.2
Saudi Arabia	SAU	Type 2: Powerhouses	144.7	251.6	73.9
Slovenia	SVN	Type 2: Powerhouses	116.4	115.7	−0.6
Switzerland	CHE	Type 2: Powerhouses	84.2	115.3	36.9
Thailand	THA	Type 2: Powerhouses	N/A	57.7	N/A
Turkey	TUR	Type 2: Powerhouses	123.5	196.2	58.9
United Arab Emirates	ARE	Type 2: Powerhouses	N/A	N/A	N/A
United States	USA	Type 2: Powerhouses	80.9	92.3	14.1
Vietnam	VNM	Type 2: Powerhouses	N/A	N/A	N/A
Macao	MAC	Type 3: Hyper-Dependent	64.7	57.8	−10.6
Botswana	BWA	Type 4: Value Pivoters	N/A	64.7	N/A
Eswatini	SWZ	Type 4: Value Pivoters	46.8	122.2	161.3
Guinea	GIN	Type 4: Value Pivoters	N/A	43.5	N/A
Malawi	MWI	Type 4: Value Pivoters	N/A	70.0	N/A
Mozambique	MOZ	Type 4: Value Pivoters	N/A	122.1	N/A
Namibia	NAM	Type 4: Value Pivoters	44.1	81.3	84.3
Rwanda	RWA	Type 4: Value Pivoters	N/A	130.3	N/A
Tunisia	TUN	Type 4: Value Pivoters	89.8	130.9	45.8

Table A4. Carbon decoupling and eco-efficiency matrix (RQ2).

Country	ISO	Archetype	Value Recovery (%)	CO ₂ Recovery (%)	Decoupling Elasticity	Eco-Efficiency T1 (USD/ton)	Tapio State
Finland	FIN	Type 2: Powerhouses	111.33	47.83	−6.87	1.95	Absolute Decoupling
Oman	OMN	Type 1: Emerging	105.14	78.07	−4.94	1.37	Absolute Decoupling
Switzerland	CHE	Type 2: Powerhouses	115.35	70.39	−2.46	4.65	Absolute Decoupling
Norway	NOR	Type 2: Powerhouses	114.85	85.36	−1.14	3.71	Absolute Decoupling
Jordan	JOR	Type 1: Emerging	136.56	78.74	−0.77	29.60	Absolute Decoupling
Croatia	HRV	Type 2: Powerhouses	150.64	75.73	−0.68	316.80	Absolute Decoupling
Greece	GRC	Type 2: Powerhouses	120.49	88.05	−0.68	34.30	Absolute Decoupling
Mexico	MEX	Type 2: Powerhouses	137.33	85.72	−0.49	12.60	Absolute Decoupling
Saudi Arabia	SAU	Type 2: Powerhouses	251.64	72.48	−0.35	6.70	Absolute Decoupling
Turkey	TUR	Type 2: Powerhouses	196.21	80.27	−0.33	42.30	Absolute Decoupling
El Salvador	SLV	Type 1: Emerging	235.27	80.39	−0.26	9.80	Absolute Decoupling
Panama	PAN	Type 1: Emerging	126.37	94.51	−0.24	8.50	Absolute Decoupling
Morocco	MAR	Type 2: Powerhouses	127.44	95.80	−0.18	35.30	Absolute Decoupling
Portugal	PRT	Type 2: Powerhouses	151.96	95.92	−0.10	54.30	Absolute Decoupling
Italy	ITA	Type 2: Powerhouses	118.52	100.37	0.02	10.20	Relative Decoupling
Moldova	MDA	Type 1: Emerging	202.75	105.71	0.08	3.82	Relative Decoupling

Table A4. Cont.

Country	ISO	Archetype	Value Re- covery (%)	CO ₂ Re- covery (%)	Decoupling Elasticity	Eco-Efficiency T1 (USD/ton)	Tapio State
Colombia	COL	Type 1: Emerging	145.39	109.56	0.24	3.48	Relative Decoupling
Slovenia	SVN	Type 1: Emerging	115.74	105.83	0.39	47.26	Relative Decoupling
Austria	AUT	Type 2: Powerhouses	114.10	118.32	1.27	24.05	Value Trap (Expansive)
Costa Rica	CRI	Type 2: Powerhouses	125.78	142.22	1.54	13.65	Value Trap (Expansive)
Tunisia	TUN	Type 4: Value Pivoters	130.90	152.47	1.57	9.20	Value Trap (Expansive)
Poland	POL	Type 2: Powerhouses	122.93	150.39	1.98	8.10	Value Trap (Expansive)
Hungary	HUN	Type 2: Powerhouses	121.98	152.46	2.12	17.10	Value Trap (Expansive)
Belgium	BEL	Type 2: Powerhouses	106.46	123.92	3.43	1.70	Value Trap (Expansive)
India	IND	Type 1: Emerging	116.70	217.85	5.04	1.00	Value Trap (Expansive)
Luxembourg	LUX	Type 1: Emerging	109.68	250.96	9.96	6.00	Value Trap (Expansive)
Netherlands	NLD	Type 2: Powerhouses	99.31	103.22	−4.61	2.02	Value Trap (Collapse)
Estonia	EST	Type 2: Powerhouses	94.65	121.56	−3.55	21.98	Value Trap (Collapse)
Chile	CHL	Type 2: Powerhouses	92.12	118.87	−2.11	2.17	Value Trap (Collapse)
Israel	ISR	Type 2: Powerhouses	62.44	159.43	−0.99	0.48	Value Trap (Collapse)
Paraguay	PRY	Type 1: Emerging	61.32	155.12	−0.90	2.82	Value Trap (Collapse)
Sri Lanka	LKA	Type 1: Emerging	38.97	129.57	−0.27	1.40	Value Trap (Collapse)
Germany	DEU	Type 2: Powerhouses	80.23	95.22	0.22	0.64	Economic Contraction
Peru	PER	Type 2: Powerhouses	87.72	93.17	0.54	2.93	Economic Contraction
Azerbaijan	AZE	Type 1: Emerging	62.11	70.18	0.74	3.67	Economic Contraction
Fiji	FJI	Type 1: Emerging	86.24	86.90	0.95	3.32	Economic Contraction
Argentina	ARG	Type 2: Powerhouses	87.65	59.73	3.91	1.90	Economic Contraction
Mauritius	MUS	Type 1: Emerging	98.52	79.83	15.08	12.60	Economic Contraction
Bahrain	BHR	Type 2: Powerhouses	93.52	26.45	19.83	28.90	Economic Contraction
Samoa	WSM	Type 1: Emerging	99.50	41.79	172.36	21.80	Economic Contraction
Belarus	BLR	Type 2: Powerhouses	N/A	32.40	N/A	N/A	Economic Contraction

Note: Decoupling elasticity (DE) is calculated strictly based on the standard Tapio formulation: $DE = \ln(\text{CO}_2_Rec) / \ln(\text{Value_Rec})$. Eco-Efficiency T1 represents the economic yield generated per unit of international aviation emissions (USD/ton of CO₂). Belarus (BLR) exhibits missing economic data for T1, but is classified under Economic Contraction based on its substantial contraction in aviation emission load. All financial indicators and eco-efficiency metrics are reported in nominal USD; real growth values may differ due to 2022–2023 inflation.

Table A5. Countries by strategic zone (RQ4).

Strategic Zone (Quadrant)	Tapio Environmental State	Destinations (Archetype)
Sustainable Leaders (High Resilience/High Decoupling)	Absolute Decoupling	Switzerland (Type 2), Finland (Type 2), Greece (Type 2), Croatia (Type 2), Jordan (Type 1), Morocco (Type 2), Mexico (Type 2), Norway (Type 2), Oman (Type 1), Panama (Type 1), Portugal (Type 2), Saudi Arabia (Type 2), El Salvador (Type 1), Turkey (Type 2), Austria (Type 2), Belgium (Type 2), Costa Rica (Type 2), Hungary (Type 2), India (Type 1), Luxembourg (Type 1), Poland (Type 2), Tunisia (Type 4)
Mass-Market Traps (High Resilience/Recoupling)	Value Trap (Expansive)	Colombia (Type 1), Italy (Type 2), Moldova (Type 1), Slovenia (Type 2), Chile (Type 2), Estonia (Type 2), Israel (Type 2), Sri Lanka (Type 1), Netherlands (Type 2), Paraguay (Type 1), Argentina (Type 2), Azerbaijan (Type 1), Bahrain (Type 2), Germany (Type 2), Fiji (Type 1), Mauritius (Type 1), Peru (Type 2), Samoa (Type 1)
Value Pivoters (Low Resilience/High Decoupling)	Relative Decoupling	
Vulnerable Laggards (Low Resilience/Recoupling)	Value Trap (Collapse)	
-	Economic Contraction	

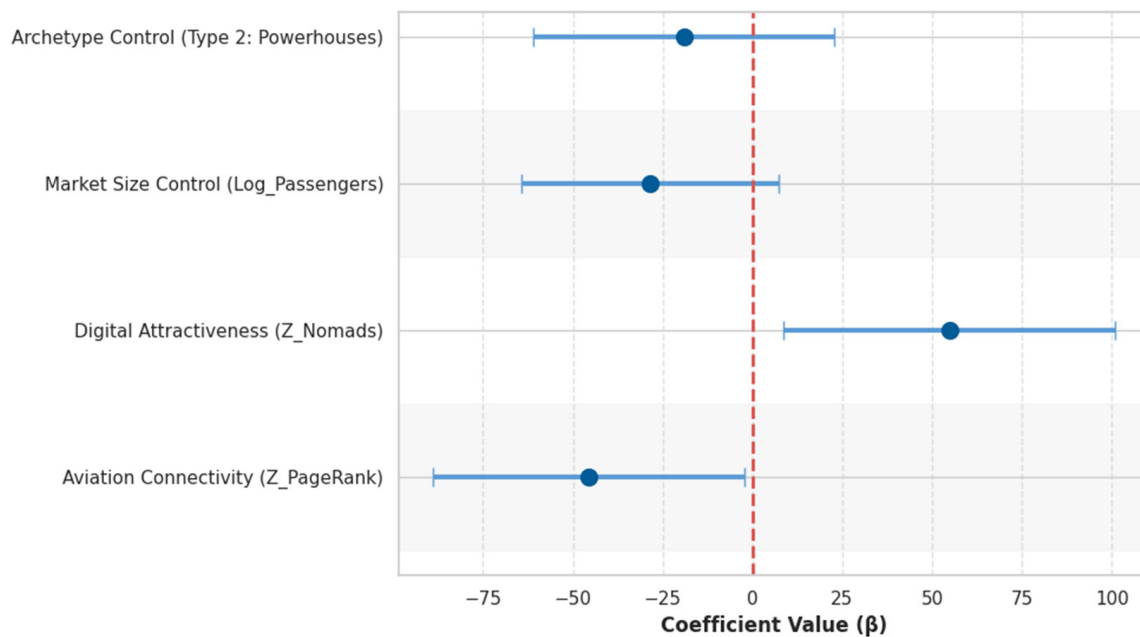


Figure A1. OLS standardized coefficients and 95% confidence intervals for recovery accelerators (RQ3).

References

1. Agyeiwaah, E.; McKercher, B. Developing a Thriving Domestic Tourism Sector in Emerging Economies: A Horizon 2050 Paper. *Tour. Rev.* **2025**, *80*, 28–38. [\[CrossRef\]](#)
2. Duro, J.; Perez-Laborda, A.; Fernandez, M. Territorial Tourism Resilience in the COVID-19 Summer. *Ann. Tour. Res. Empir. Insights* **2022**, *3*, 100039. [\[CrossRef\]](#)
3. Krabokoukis, T. Exploring the State of Research on Tourism Sustainability: A Bibliometric Analysis in the Post-COVID Era. *Highlights Sustain.* **2023**, *2*, 50–61. [\[CrossRef\]](#)
4. Krabokoukis, T.; Kantianis, D. Evolution of Management Research in Greece: A Comparative Analysis of 2014–2018 and 2019–2023 Trends. *J. Knowl. Econ.* **2024**, *16*, 9752–9775. [\[CrossRef\]](#)
5. Poutakidou, G.; Menegaki, A.N. Do Energy Prices Put the Tourism Sector at Risk? *Economies* **2023**, *11*, 197. [\[CrossRef\]](#)
6. Hu, P.; Wang, D.D. The Impact of War on Tourism: A Synthetic Control and Causal Configuration Analysis. *Ann. Tour. Res.* **2025**, *114*, 104014. [\[CrossRef\]](#)
7. Wang, Y.; Han, L.; Ma, X. International Tourism and Economic Vulnerability. *Ann. Tour. Res.* **2022**, *94*, 103388. [\[CrossRef\]](#)
8. Nishkar Kumar, N.; Patel, A. A Test of the Tourism Dutch Disease Hypothesis in Developing Countries. *J. Air Transp. Manag.* **2024**, *116*, 102577. [\[CrossRef\]](#)
9. Tuncay, N.; Özcan, C.C. The Effect of Dutch Disease in the Tourism Sector: The Case of Mediterranean Countries. *Tour. Hosp. Manag.* **2020**, *26*, 97–114. [\[CrossRef\]](#)
10. Afonso, O.; Vasconcelos, P.B.; Pinto, L. Is Tourism the New Dutch Disease? Impacts on Wages, Sectorial Competitiveness and Economic Growth. *J. Dyn. Games* **2025**, *12*, 465–483. [\[CrossRef\]](#)
11. UN Tourism. UN Tourism World Tourism Barometer. Available online: <https://www.untourism.int/un-tourism-world-tourism-barometer-data> (accessed on 29 June 2026).
12. Koh, E. The End of Over-Tourism? Opportunities in a Post-COVID-19 World. *Int. J. Tour. Cities* **2020**, *6*, 1015–1023. [\[CrossRef\]](#)
13. Lin, W.-C.; Wu, C.K.; Le, T.K.T.; Nguyen, N.A. Assessment of Vietnam Tourism Recovery Strategies after COVID-19 Using Multi-Criteria Decision-Making Approach. *Sustainability* **2023**, *15*, 10047. [\[CrossRef\]](#)
14. Cai, J.; Wang, C.; Hu, H.; Ho, W.I.; Chan, K.I.; Yin, Y. Resilience or Mirage? Deconstructing the Economic Recovery and Labor Market Structural Lag in Macao's Tourism Sector. *Tour. Hosp.* **2026**, *7*, 10. [\[CrossRef\]](#)
15. Muñoz-Barriga, A.; Öckler, A.; Andrade, E.D.; Rojas, K. From Pre-Pandemic to Post-COVID-19: Tracking Shifts in Visitors' Profiles in Santa Cruz, Galapagos. *Sustainability* **2025**, *17*, 8302. [\[CrossRef\]](#)
16. Scuttari, A.; Windegger, F.; Wallnöfer, V.; Pechlaner, H. Bridging the Science-Policy Gap in Sustainable Tourism: Evidence from a Multiple Case Study Analysis of UNWTO INSTO Sustainable Tourism Observatories. *J. Sustain. Tour.* **2025**, *33*, 628–652. [\[CrossRef\]](#)

17. Toanoglou, M.; Krabokoukis, T.; Papadimitriou, E. A Comparative Analysis of Tourism Observatories within the INSTO Network: Insights into Regional Approaches to Sustainability, Methodology, Stakeholder Engagement, and Technological Innovation. *Athens J. Tour.* **2025**, *12*, 117–144. [\[CrossRef\]](#)
18. Jiao, X.; Li, G.; Qiu, R.T.R.; Chen, J.L. Analyzing Destination Resilience From A Spatiotemporal Perspective. *J. Travel Res.* **2025**, *64*, 1186–1205. [\[CrossRef\]](#)
19. Ríos Rodríguez, N.; Nieto Masot, A.; Cárdenas Alonso, G. Impact of the COVID-19 Pandemic on Tourism: A Clustering Approach for the Spanish Tourism Analysis. *Land* **2023**, *12*, 1494. [\[CrossRef\]](#)
20. Tsiotas, D.; Krabokoukis, T.; Kantianis, D. Regional Economic Resilience and Tourism Demand: The Case of Greece. *Reg. Sci. Inq.* **2025**, *17*, 101–116.
21. Sharma, G.D.; Thomas, A.; Paul, J. Reviving Tourism Industry Post-COVID-19: A Resilience-Based Framework. *Tour. Manag. Perspect.* **2021**, *37*, 100786. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Hampton, M.P.; Jeyacheya, J.; Nair, V. Post-COVID Tourism Revealed: Evidence from Malaysia. *Ann. Tour. Res.* **2023**, *103*, 103671. [\[CrossRef\]](#)
23. Wickramasinghe, K.; Naranpanawa, A. Tourism and COVID-19: An Economy-Wide Assessment. *J. Hosp. Tour. Manag.* **2023**, *55*, 131–138. [\[CrossRef\]](#)
24. Dobre, C.; Toma, E.; Linca, A.-C.; Iorga, A.M. Rural Tourism Recovery Patterns in the Eastern Carpathians: A Cluster-Based Approach. *Sustainability* **2025**, *17*, 4576. [\[CrossRef\]](#)
25. Wąsowicz-Zaborek, E. Workation as a New Mode of Work—Analysis of Top European Destinations. *Bull. Geogr. Socio-Econ. Ser.* **2025**, *68*, 159–174. [\[CrossRef\]](#)
26. Deng, Z.; Zhou, M.; Xu, Q. How to Decouple Tourism Growth from Carbon Emissions? A Spatial Correlation Network Analysis in China. *Sustainability* **2022**, *14*, 11961. [\[CrossRef\]](#)
27. Yan, H.; Ligu, W.; Hai, Z.; Wei, S.; Xinyue, Z. Tourism Carbon Emission Forecasting, the Decoupling Effect and Its Driving Factors in the Yangtze River Economic Belt under the “Double Carbon” Target. *J. Resour. Ecol.* **2023**, *14*, 1329–1343. [\[CrossRef\]](#)
28. Guo, T.; Wang, J.; Li, C. Spatial–Temporal Evolution and Influencing Mechanism of Tourism Ecological Efficiency in China. *Sustainability* **2022**, *14*, 16880. [\[CrossRef\]](#)
29. Rahawarin, M.F.; Mizuno, K.; Karuniasa, M. Tourism Eco-Efficiency: Progress and Prospect. *Turyzm/Tourism* **2025**, *35*, 175–192. [\[CrossRef\]](#)
30. Arslan, E. From Tourists to Nomads: Unveiling the Transformative Potential of Digital Nomads in Travel and Tourism. *Worldw. Hosp. Tour. Themes* **2024**, *16*, 269–281. [\[CrossRef\]](#)
31. Hannonen, O. Emergent Geographies of Digital Nomadism: Conceptual Framing, Insights and Implications for Tourism. *Tour. Geogr.* **2025**, *27*, 568–578. [\[CrossRef\]](#)
32. Kc, H.; Triandafyllidou, A. Digital Nomadism and the Emergence of Digital Nomad Visas: What Policy Objectives Do States Aim to Achieve? *Int. Migr. Rev.* **2026**, *60*, 71–92. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Tian, Y. Study on the Impact of Carbon Emission Pollution on Urban Tourism Environment. *Eng. Rep.* **2023**, *5*, e12641. [\[CrossRef\]](#)
34. Leal Filho, W.; Ng, A.W.; Sharifi, A.; Janová, J.; Özuyar, P.G.; Hemani, C.; Heyes, G.; Njau, D.; Rampasso, I. Global Tourism, Climate Change and Energy Sustainability: Assessing Carbon Reduction Mitigating Measures from the Aviation Industry. *Sustain. Sci.* **2023**, *18*, 983–996. [\[CrossRef\]](#) [\[PubMed\]](#)
35. Doreen, K.; Muhaise, H.; Christine, A. Digital Nomads as a Viable Market Segment: A Systematic Literature Review. *Afr. J. Tour. Hosp. Manag.* **2025**, *4*, 379–389. [\[CrossRef\]](#)
36. Zhou, L.; Buhalis, D.; Fan, D.X.F.; Ladkin, A.; Lian, X. Attracting Digital Nomads: Smart Destination Strategies, Innovation and Competitiveness. *J. Destin. Mark. Manag.* **2024**, *31*, 100850. [\[CrossRef\]](#)
37. Bednorz, J. Working from Anywhere? Work from Here! Approaches to Attract Digital Nomads. *Ann. Tour. Res.* **2024**, *105*, 103715. [\[CrossRef\]](#)
38. Cohen, S.; Hannonen, O. A Review of Research into Lifestyle Mobilities and Digital Nomadism. *Ann. Tour. Res.* **2026**, *116*, 104067. [\[CrossRef\]](#)
39. Sun, Y.-Y.; Faturay, F.; Lenzen, M.; Gössling, S.; Higham, J. Drivers of Global Tourism Carbon Emissions. *Nat. Commun.* **2024**, *15*, 10384. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Gössling, S.; Humpe, A.; Sun, Y.-Y. Are Emissions from Global Air Transport Significantly Underestimated? *Curr. Issues Tour.* **2025**, *28*, 695–708. [\[CrossRef\]](#)
41. United Nations Environment Programme (UNEP). Resource Efficiency and Eco-Efficiency. Available online: <https://www.unep.org/> (accessed on 29 June 2026).
42. Humpe, A.; Gössling, S.; Bernard, S.; Sonntag, U. Boomer Tourism and Climate Change: An Emerging Conflict? *Curr. Issues Tour.* **2025**, 1–19. [\[CrossRef\]](#)
43. Wang, Q.; Tang, Q.; Guo, Y. Spatial Interaction Spillover Effect of Tourism Eco-Efficiency and Economic Development. *Sustainability* **2024**, *16*, 8012. [\[CrossRef\]](#)

44. World Economic Forum. *Travel & Tourism Development Index 2024*; World Economic Forum: Cologny, Switzerland, 2024.
45. Krabokoukis, T. Bridging Neuromarketing and Data Analytics in Tourism: An Adaptive Digital Marketing Framework for Hotels and Destinations. *Tour. Hosp.* **2025**, *6*, 12. [CrossRef]
46. Sukma, A.; Rochman, D.D.; Murnawan; Nugraha, U.; Anggakarti, D.M. How Digital Technology Shapes Traveller Awareness and Engagement in Sustainable Tourism in Indonesia. *Soc. Sci. Humanit. Open* **2025**, *12*, 102072. [CrossRef]
47. Statista Most Visited Countries by Digital Nomads Worldwide. Available online: <https://www.statista.com/statistics/1298983/most-visited-countries-by-digital-nomads-worldwide/> (accessed on 29 June 2026).
48. World Travel & Tourism Council. *The Future of Work in Travel & Tourism: The Key Trends Shaping Workforce Strategies*; World Travel & Tourism Council: London, UK, 2025. Available online: <https://researchhub.wttc.org/product/the-future-of-work-in-travel-tourism-the-key-trends-shaping-workforce-strategies> (accessed on 29 June 2026).
49. O'Connor, M.-J.; Yilmaz, B.; Borgers, N.; Fedotova, Z. Tourism Workforce Trends in Europe: Employment Patterns, Regulation, and Recovery. *Munich Personal RePEc Archive*, 2025. Available online: https://mpa.ub.uni-muenchen.de/126180/1/MPRA_paper_126180.pdf (accessed on 29 June 2026).
50. Driha, O.M.; Cascetta, F.; Nardini, S.; Bianco, V. Decomposition and Decoupling Analysis of Carbon Emissions of the EU Tourism Sector. *Sci. Total Environ.* **2025**, *994*, 180075. [CrossRef] [PubMed]
51. Maurya, P.K.; Ali, S.A.; Ahmad, A.; Zhou, Q.; Da Silva Castro, J.; Khane, E.; Ali, A. An Introduction to Environmental Degradation: Causes, Consequence and Mitigation. In *Environmental Degradation: Causes and Remediation Strategies*; Agro Environ Media-Agriculture and Ennvironmental Science Academy: Haridwar, India, 2020; pp. 1–20.
52. Shang, M.; Luo, J. The Tapio Decoupling Principle and Key Strategies for Changing Factors of Chinese Urban Carbon Footprint Based on Cloud Computing. *Int. J. Environ. Res. Public. Health* **2021**, *18*, 2101. [CrossRef] [PubMed]
53. Buhalis, D.; Sinarta, Y. Real-Time Co-Creation and Nowness Service: Lessons from Tourism and Hospitality. *J. Travel Tour. Mark.* **2019**, *36*, 563–582. [CrossRef]
54. ForwardKeys Remote Work, Real Opportunity: How Digital Nomads Are Reshaping Global Tourism. Available online: <https://forwardkeys.com/remote-work-real-opportunity-how-digital-nomads-are-reshaping-global-tourism/> (accessed on 29 June 2026).
55. URBACT Digital Nomads and Sustainable Tourism: How Can Remote Work Support More Balanced, Year-Round Tourism? Available online: <https://urbact.eu/digital-nomads-and-sustainable-tourism-how-can-remote-work-support-more-balanced-year-round-tourism> (accessed on 29 June 2026).
56. Palazzo, M.; Gigauri, I.; Panait, M.C.; Apostu, S.A.; Siano, A. Sustainable Tourism Issues in European Countries during the Global Pandemic Crisis. *Sustainability* **2022**, *14*, 3844. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.