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Oil Prices, Environmental Protection, and India's LCT Exports to OECD Markets: A Gravity Model Approach

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Amidst heightened concerns over cross-border transfer of cleaner and greener products, this paper examines how oil import price fluctuations and environmental protection expenditure in OECD countries influence India's low-carbon-technology (LCT) exports, aligned with SDG 7, SDG 13, and SDG 17. Employing a Poisson Pseudo Maximum Likelihood estimator with a structural gravity model for 24 OECD countries between 2002–2021, the analysis uncovers asymmetric dynamics. Rising oil import prices significantly stimulate India's LCT exports through heightened demand for energy substitutes, whereas increased OECDs' environmental protection expenditure suppresses imports by virtue of enhanced domestic green manufacturing capacities. These findings challenge the conventional assumption that greater environmental expenditure universally expands global clean-tech trade. India's export competitiveness in solar PV, wind, and EV components underscores its potential to leverage OECD's China+1 diversification strategies and trade realignments. Policy coherence with Sustainable Development Goals (SDGs) standards, R&D intensity, and multilateral climate cooperation emerges as critical for sustaining LCT export growth.

Keywords: LCT exports, SDG-7, gravity model, OECD countries, environmental protection expenditure, oil imports, PPML estimation

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Introduction

The global shift toward decarbonization has redefined the strategic significance of low-carbon technologies (LCTs) in international trade, particularly for emerging economies such as India (International Monetary Fund 2022). Energy markets are facing increasing volatility and climate

policy is gaining momentum, so understanding how external energy price shocks and environmental spending commitments influence green trade flows has become essential. As countries strive to meet ambitious climate targets under frameworks such as the Paris Agreement and, more recently, CBAM (Carbon Border Adjustment Mechanisms), demand for green technologies – spanning renewable energy systems, energy-efficient machinery, electric vehicles, and carbon mitigation tools – has surged.

For emerging economies like India, this represents a strategic export opportunity to integrate into high-value global green value chains. India has rapidly expanded its LCT capabilities over the past decade, with firms increasingly exporting solar components, smart grid equipment, and clean energy solutions. Yet, the external determinants of India's LCT export performance remain underexplored in the empirical literature, especially in relation to demand-side variables in destination countries. Among India's key trading partners, the OECD countries stand out for aligning their import demand with and increasing their investments in environmental protection and climate mitigation.

This paper explores the dual impact of rising oil import prices and public environmental protection expenditures by 24 OECD countries (selected as per data availability) on India's exports of low-carbon technologies to them over a period of 20 years, using reduced-form of the structural gravity model estimated via Poisson Pseudo Maximum Likelihood (PPML). The study hypothesizes that higher oil prices may raise the relative competitiveness of LCT products by increasing the cost of fossil-based alternatives, while increased environmental expenditure signals policy-driven demand for clean technologies – both factors potentially spurring LCT imports from technologically capable partners like India. However, the results obtained are counterintuitive and enlightening. This inquiry is situated at the intersection of three strands of literature: energy prices and green innovation, the role of environmental policy in shaping trade, and empirical gravity models applied to environmental goods. The study reinforces the critical role of international trade in low-carbon technologies as a mechanism for advancing access to clean, modern energy systems serving as a trigger for accelerated clean energy adoption – a dynamic that India, as a low-cost green technology supplier, can leverage to support SDG 7. Promoting LCT exports from developing economies contributes to global emissions reductions, aligning with SDG 13 on climate actions. The study's recommendations for enhancing trade

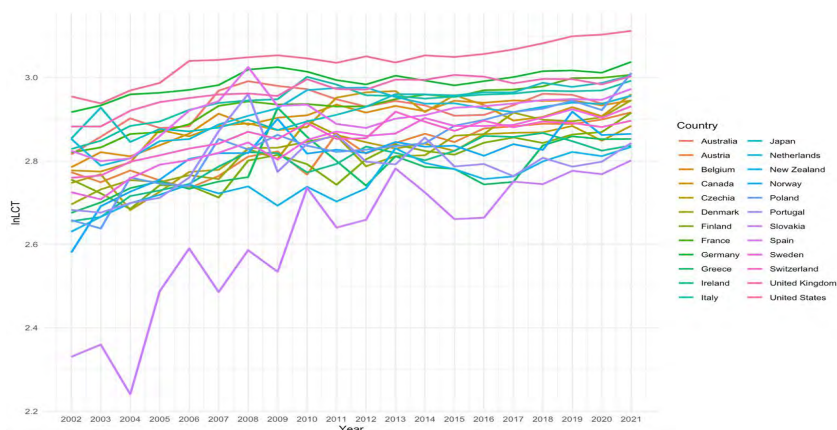


FIGURE 1 Trend Plot of LCT Exports from India to the 24 OECDs Over the Period 2002–21

diplomacy, mutual recognition of environmental standards, and bilateral cooperation align closely with SDG 17, which advocates for equitable trade and export promotion from developing countries.

A longitudinal perspective of Indian LCT exports to the OECD countries in the line chart in figure 1 from 2002 to 2021 confirms an unambiguous increase. During the early 2000s, most nations had comparatively modest levels of Indian imports of LCTs. But from around 2010, the evidence indicates an obvious speeding up. It is a period when there was growing international policy attention to addressing climate change, the dissemination of renewable energy objectives, and Indian investment in significant clean technology production capacity. By 2021, the aggregate magnitude of LCT exports is much larger than at the beginning of the sample period. Not only does the growth persist, but it also appears to be resilient to short-term economic shocks like the global financial crisis and the COVID-19 pandemic, suggesting that Indian LCT exports became more and more integrated into value chains globally.

In the context of a global energy transition, this study's conclusions have significant ramifications for the OECD's import planning as well as India's export strategies. Finding that crude oil prices are a major factor in LCT exports gives India a definite tool for promoting exports. Concurrently, when developed countries like the OECDs increase expenditure on environmental protection, it often coincides with tighter environmental regulations and stricter product standards for energy efficiency and recyclability, implying that if LCT products coming from develop-

ing countries like India fail to meet these heightened environmental or sustainability criteria, they may be barred from the market or subject to *non-tariff barriers* (NTBs), such as compliance certifications, testing, or eco-labelling requirements. The resulting reduced demand for LCT exports acts as a lesson for policy makers in India to aim for upgrading the product quality of such green exports to successfully boost export-led-growth performances. OECD nations are under increasing pressure to separate their industrial and energy systems from the volatility of fossil fuels as oil prices rise. With its existing manufacturing capabilities and policy incentives, India has a window of opportunity to establish itself as a dependable and affordable LCT supplier, particularly in industries like solar photovoltaic (PV) systems, smart grids, and energy-efficient devices.

The rest of the paper is organized as follows. The second section provides the theoretical framework that conceptualizes the constructs, reviews the literature further and proposes the hypotheses to be tested. The third section discusses the methodology, the variables of the study and the data sources. The fourth section presents the PPML estimation results. The fifth section interprets the empirical findings and, finally, the sixth section highlights the policy considerations and concludes the paper.

Theoretical Framework

The relationship between oil prices and green innovation has generated extensive debate. One strand of literature argues that rising fossil fuel prices act as a market-based stimulus for clean technology adoption by improving the relative competitiveness of low-carbon alternatives. Popp (2002) and Aghion et al. (2016) show that energy price shocks significantly spur innovation and deployment of renewable technologies. For oil-importing countries, such shocks often lead to a reorientation of energy portfolios toward renewables, stimulating trade in green technologies (Doda 2014; El-Karimi 2022; Shadab 2025; Adekunle 2025). Conversely, periods of low oil prices weaken incentives to shift towards cleaner alternatives, potentially dampening demand for green exports. Despite substantial evidence from developed economies, the implications of oil price dynamics for low-carbon technology (LCT) exports from emerging economies such as India remain underexplored.

Parallel to energy price dynamics, environmental protection expenditure by OECD governments has emerged as a key proxy for green policy commitment. Such spending – covering pollution abatement, renewa-

ble subsidies, environmental R&D, and green infrastructure – has been shown to stimulate both innovation and trade in environmental goods, particularly when supported by regulatory frameworks and green procurement policies (Johnstone et al. 2010; Costantini and Mazzanti 2012; Bryngemark et al. 2023; Gisselman et al. 2025; Dechezleprêtre and Sato 2017; Binh et al. 2025). These expenditures foster domestic demand for LCT imports and enhance market opportunities for exporters. They capture the fiscal effort and policy intensity of countries in reducing environmental externalities. However, one cannot ignore an exact opposite line of explanation of a possible negative relationship. Rising environmental expenditure reflects strong domestic industrial policy channelled towards building domestic LCT manufacturing capacity, subsidizing local firms, and strengthening innovation ecosystems, thereby reducing dependence on external suppliers such as India.

A growing body of literature highlights international trade as a crucial channel for the diffusion of LCTs, central to sustainable development. Cobbold et al. (2024), using data from 32 countries (1996–2020), find that LCT imports stimulate domestic green innovation, with stronger effects when supported by environmental policies such as green taxes. Trade also enhances foreign direct investment and knowledge spillovers, reinforcing innovation ecosystems. Tran (2022), employing a generalized synthetic control method, demonstrates that ratification of the Kyoto Protocol increased environmental goods exports by 31–32%, indicating that multilateral climate agreements can reshape comparative advantages and boost green trade. Nyasha (2024), motivated by Zimbabwe's commitment to reducing greenhouse gas emissions and expanding renewable energy while assessing whether such energy use can also stimulate economic recovery, uses annual data from 1990–2019 and an ARDL model to show that renewable energy consumption positively influences economic growth in both the short and long run. Together, these studies underline how trade openness, climate regulation, and Intellectual Property Rights (IPR) regimes jointly facilitate cross-border diffusion of green technologies.

Empirical evidence also suggests that greater trade openness accelerates LCT diffusion. Pigato et al. (2020) show that tariff reductions significantly boost LCT imports, while binding climate policies further strengthen this effect. However, despite extensive literature on fossil fuel prices and renewable energy consumption, there is only limited work examining how crude oil import prices influence LCT trade flows. This

gap is significant given the evolving global structure of LCT production. While China dominates global supply – accounting for around 80% of solar PV cells and EV (electric vehicle) battery production – India has emerged as a critical alternative supplier within the ‘China +1’ strategy. High US tariffs on Chinese goods, coupled with relatively lower tariffs on Indian products, have enhanced India’s competitiveness. Indian PV exports increased over 23-fold between FY 2022 and FY 2024, with the US absorbing over 97% of these exports. Government initiatives such as the Production Linked Incentive (PLI) scheme have further strengthened India’s export capacity. OECD countries remain heavily dependent on oil imports, and the post-Ukraine war energy price surge has reinforced the urgency to reduce fossil fuel dependence for both environmental and energy security reasons. Policy measures such as the EU Green Deal aim to subsidize clean energy and penalize carbon-intensive imports, while US tariffs on Chinese goods have created protected demand for non-Chinese LCTs. In this context, India’s role as a low-cost, innovation-driven exporter of solar modules, EV components, and energy-efficient technologies is growing but remains insufficiently examined in empirical trade literature.

Although India’s domestic green industrial policies have received attention, its bilateral green trade dynamics with advanced economies have rarely been investigated using rigorous econometric approaches. This is particularly notable given rising OECD environmental ambition, including mechanisms such as the EU’s Carbon Border Adjustment Mechanism (CBAM) and expanded green procurement policies. Addressing this gap, the present study examines how external macroeconomic forces (specifically oil import prices) and institutional environmental commitment (proxied by environmental protection expenditure) jointly shape India’s LCT exports to OECD countries. In doing so, it contributes to a more nuanced understanding of the evolving geography of the global green technology trade.

Based on the above literature and theoretical rationale, the study proposes the following hypotheses:

- H1 Higher international oil prices are positively associated with India’s LCT exports to OECD countries.
- H2 Increased public expenditure on environmental protection by OECD countries may accelerate or dampen their imports of LCTs from India.

Environmental protection expenditure, however, is not a homogeneous policy instrument. Under the COFOG (Classification of the Functions of Government), it includes heterogeneous components such as waste management, pollution abatement, biodiversity protection, environmental infrastructure, and environmental research and development. These components may have different implications for international trade: while public procurement of environmental infrastructure may stimulate imports of environmental goods, expenditures directed toward domestic R&D or industrial subsidies may strengthen local production capacity and reduce reliance on foreign suppliers. This implies that the ambiguity is not a surprise but an empirical outcome of competing mechanisms.

In order to empirically test these relationships, we employ a structural gravity model with Poisson Pseudo-Maximum Likelihood (PPML) estimation, which effectively manages zero trade flows and heteroskedasticity while maintaining the multiplicative functional form of the gravity equation. We create a panel dataset that spans 20 years, from 2002 to 2021, for 24 selected OECD economies, based on data availability. Our key findings reveal a significant positive association between crude oil import prices and India's LCT exports. This finding supports hypothesis H1 that high oil prices – through both energy security and substitution effects – encourage greater demand for clean technologies, thus improving India's export performance in the sector. However, there exists an inverse relationship between OECD nations' environmental protection spending (EEP) and Indian LCT exports. While one would expect higher environmental spending to simulate higher LCT imports, the evidence suggests otherwise. We lay out the plausible underlying reasoning, including domestic capacity building, shifting regulatory standards, trade policy innovations, and shifts in market preferences, in the later parts of the paper.

Methodology, Variables and Data Sources

THE STRUCTURED GRAVITY MODEL

The pioneering work of Tinbergen (1962) that developed the gravity model of international trade has been the standard econometric specification for trade empiricists to analyse and predict bilateral trade flows. The gravity framework remains the empirical workhorse in international trade analysis, offering a robust structure to model trade flows based

on exporter-importer characteristics and dyadic trade frictions. The structured gravity model extends the traditional multiplicative gravity equation by incorporating internal consistency with economic principles such as firm-level heterogeneity and market structure. Rooted in trade theory and consistent with Anderson and van Wincoop (2003), this model allows for a theory-driven analysis of bilateral trade flows, capturing both economic mass and bilateral resistance terms. In its structural form, it explicitly accounts for multilateral resistance terms and enables incorporation of policy variables (such as environmental expenditure) and macroeconomic shocks (like oil import price changes) within a coherent econometric setup. The general specification of the structured gravity equation is given as (Krisztin and Fischer 2015):

$$X_{ij} = \frac{E_i^\sigma}{P_i^{1-\sigma}} \frac{Y_j}{P_j^{1-\sigma}} \phi_{ij}, \quad (1)$$

where X_{ij} represents the bilateral trade flow from exporter (i) to importer (j), E_i and Y_j are the economic sizes (GDP or output) of the exporter and importer, respectively, P_i and P_j are outward and inward multilateral resistance terms, σ represents the elasticity of substitution between goods, and ϕ_{ij} captures bilateral trade costs, often modelled as a function of geographic distance, trade agreements, tariffs, and other trade barriers.

A log-linear transformation of the gravity equation is often used in estimation. However, the presence of zero trade flows (Santos Silva and Tenreyro 2006; Helpman et al. 2008; Burger et al. 2009) poses a challenge, rendering log-linearization infeasible. Several methods have been suggested to deal with the zero flows problem, such as excluding zero trade flows from the data set and estimating the parameters of interest on the truncated sample of countries. However, this generates biased estimates due to loss of data and should be avoided (Westerlund and Wilhelmsson 2011). The approaches followed by the other empirical studies have tried to modify the dependent variable to accommodate the log transformation but ended up yielding generally inconsistent estimates, where the severity of these inconsistencies will depend on the model and the specific characteristics of the sample used. The safest alternative estimation technique employed by most of the recent studies to address heteroskedasticity and the presence of zero trade flows is the Poisson Pseudo-Maximum Likelihood (PPML) estimator introduced by Santos Silva and Tenreyro (2006). The PPML regression equation is specified as:

$$X_{ij} = \exp(\beta_0 + \beta_1 Z_{ij} + \gamma_i + \delta_j) + \varepsilon_{ij}, \quad (2)$$

where Z_{ij} is a vector of bilateral trade cost variables (distance, common language, shared border, trade agreements, etc.), γ_i and δ_j are exporter and importer fixed effects capturing multilateral resistance terms, and ε_{ij} is the error term.

PPML estimation proceeds by solving the following first-order condition:

$$\sum_{ij} (X_{ij} - \hat{X}_{ij}) Z_{ij} = 0, \quad (3)$$

$$\text{where } \hat{X}_{ij} = \exp(\hat{\beta}_0 + \hat{\beta}_1 Z_{ij} + \hat{\gamma}_i + \hat{\delta}_j) \quad (3.1)$$

Unlike OLS, which assumes additive errors and ignores zero trade flows, PPML models trade flows in levels and provides a robust and consistent estimation framework under multiplicative error forms that is standard in gravity models.

VARIABLES AND DATA SOURCES

Specifically, in our case, to examine the impact of oil import prices and environmental protection expenditure of the OECD countries on the export value of LCT products from India, the following PPML estimation specification is constructed based on the reduced-form gravity model:

$$\begin{aligned} X_{jt} = \exp & (\beta_0 + \beta_1 OIP_{jt} + \beta_2 EPP_{jt} + \beta_3 GDP_{jt} + \beta_4 DIST_{jt} \\ & + \beta_5 POP_{jt} + \beta_6 LANG_{jt} + \beta_7 TER_{jt} + \beta_8 REER_{jt} \\ & + \beta_9 WGI_{jt} + \beta_{10} REC_{jt} + \delta_j + \phi_t) + \varepsilon_{ijt}, \end{aligned} \quad (4)$$

where the dependent variable X_{ijt} is the natural flow of LCT exports from India to the j^{th} destination OECD country in period t (in years), and the two primary explanatory variables are OIP_{jt} , that captures the oil import prices, and EPP_{jt} , which is the expenditure on environmental protection faced by the OECD countries. Control variables typically used in gravity models are also included: the annual growth rate of Gross Domestic Product (GDP_{jt}) reflects the economic size of the importing partner; $DIST_{jt}$ measures the geographical distance of the j^{th} country from India, representing transportation costs; POP_{jt} indicates the annual growth rate of the population, representing the potential market size; and $LANG_{jt}$ is a dummy variable that equals 1 if India and the j^{th} OECD country share

a common official language, and o otherwise, capturing communication-related trade facilitation.¹

In addition to these, the specification in Equation (4) incorporates a few more factors that also influence LCT exports based on the relevant literature: TER_{jt} refers to the enrolment ratio (gross) in tertiary education; $REER_{jt}$ represents the Real Effective Exchange Rate between India and the j^{th} importing country; WGI_{jt} stands for World Governance Indicators, reflecting the institutional quality level of the j^{th} importing country; and REC_{jt} is the renewable energy consumption as a percentage of total final energy consumption. Higher tertiary education enrolment increases technological absorptive capacity and environmental awareness within importing economies. Countries with more skilled labour forces are better positioned to adopt and integrate advanced low-carbon technologies, which can stimulate demand for imported clean technology. Renewable energy consumption captures the intensity of the energy transition within importing countries. Higher renewable penetration reflects investments in clean energy infrastructure that often require complementary imported technologies, components, and equipment, thereby influencing bilateral trade flows in LCT products. β_o is the constant term and β_k (where $k = 1, \dots, 10$) are the corresponding coefficients to be estimated; δ_j captures imported fixed effects, controlling for time-invariant inward multilateral resistance across OECD markets; φ_t are the time fixed effects that proxy export-year shocks² affecting India's overall export supply; and ε_{jt} is the error term. Time fixed effects also absorb common global shocks affecting all trade relationships in a given year, including global supply-chain disruptions, tariff escalations, or broad industrial policy shifts influencing clean-technology markets. By controlling for these time-specific factors, the estimation isolates the variation arising from differences in oil price exposure and environmental expenditure across OECD importing countries. In order to improve the normality, reduce variability, and improve the linearity of the independent variables, the natural logarithmic value of all the variables excepting the dummy has been considered. So, the estimates of the coefficients corresponding to the log-transformed variables can now be interpreted as the semi-elasticities. We proceed to brief on the data sources.

India's exports of LCT products to OECD economies is sourced from the IMF Climate Change Dashboard, which offers annual trade values in USD for each country-year pair. To get real values, all figures are deflated using the US Consumer Price Index (CPI). Carbon capture systems,

wind turbines, solar panels, and biomass equipment are a few examples. The product classification suggested by Howell et al. (2023), which associates 124 5-digit HS codes (2017 revision) with LCT products, is the basis for the reported trade data. According to OECD and Eurostat (1999), these technologies constitute a particular subset of the larger category of 'environmental goods'. Crude oil import prices are obtained from the IEA's Crude Oil Import Register, which is accessed through the OECD Data Explorer. These prices not only mirror global supply and demand patterns but are also influenced by geopolitical events and energy market changes. The total import value, as reported by customs officials for each tariff line, is divided by the corresponding import volume to determine the average import price. The real price was calculated using the deflator for GDP at market prices. The IMF's Climate Change Indicators Dashboard, which uses the Government Finance Statistics (GFS) database, provides data on government spending on environmental protection by the OECD countries. According to the COFOG framework, this variable records public spending on a variety of environmental initiatives such as waste and wastewater management, pollution reduction, biodiversity and landscape preservation, and associated environmental research and development. To ensure temporal comparability, the study's measure is the total amount of money spent by the government on environmental protection, expressed in constant prices. The information offers a uniform and globally comparable indicator of environmental policy commitment across nations.

Among the control variables, the annual GDP growth rate is obtained from the World Bank's World Development Indicators (WDI) database. Expressed in constant 2015 USD for cross-country comparability, it reflects annual percentage growth at market prices. The bilateral distance between India and each destination country, proxied by capital-to-capital distance, is sourced from the CEPII GeoDist database and serves as a standard trade cost proxy in gravity models. The Common Official Language dummy variable is also sourced from CEPII and annual population growth rate data (percent) are obtained from the WDI database.

Tertiary education enrolment (TER – percent of the relevant age group) is sourced from the WDI, as higher enrolment in OECD importers fosters an environmentally conscious, technologically absorptive market (Castellacci and Lie 2017; Cohen and Levinthal 1990), supporting demand for imported greener imports. The Composite World Governance Indicators (WGI), constructed as the arithmetic mean of six governance

dimensions – voice and accountability, political stability, government effectiveness, regulatory quality, rule of law, and control of corruption – are drawn from the World Bank dataset. Stronger governance in OECD countries promotes credible environmental regulation and institutional capacity, enhancing LCT import demand (Fredriksson and Svensson 2003; Porter and van der Linde 1995; Koźluk and Timiliotis 2016). The Real Effective Exchange Rate (REER) from WDI captures India's external price competitiveness, where currency depreciation boosts LCT exports and appreciation suppresses demand. Finally, renewable energy consumption (REC) – measured as the share of renewables in total final energy use from WDI – acts as a demand-side driver for LCTs, indicating investment in clean infrastructure and energy transition.

Empirical Analysis

EXPLORATORY EVALUATION

The empirical analysis begins by examining the general behaviour of our variables. The summary statistics are computed as in table 1 for a preliminary overview.

The shape of the LCT imports distribution is symmetric with a mean and median of 16.61 and 16.62, respectively, which corresponds to a very balanced distribution. The range of the LCT imports is between 8.40 and 21.46, and the inter-quartile range (15.46 to 17.94) indicates that most of the observations are clustered around the mean. The negative skewness (−0.50) reflects the presence of a slight left tail, meaning that while most of the countries import large to medium amounts of LCTs, there are some instances of relatively lower amounts of imports. The kurtosis measure (4.20) is greater than that of the normal distribution, which reflects the presence of the heavier tails and higher probability of extreme observations, though the latter are not dominant. The variable Oil Import Prices (OIP) also follows a symmetric distribution with mean value 4.15 and median value 4.18. The minimum and maximum values of OIP are 3.19 and 4.78, respectively, and most of the values lie between the first (3.92) and third (4.52) quartiles. The negative value of skewness (−0.43) and moderate value of kurtosis (2.52), indicating weak left tail and relatively normal distribution, reflect that extreme oil price volatility is uncommon in the sample. The parallelism of the distributional characteristics of the LCT imports and OIP is striking. Both series are extremely close in their means and medians, and both are only moderately negatively skewed.

TABLE 1 Summary Statistics of the Study Variables

Variable	Min	First_ Quantile	Median	Mean	Third_ Quantile	Max	Skewness	Kurtosis
LCT	8.40	15.46	16.62	16.61	17.94	21.46	-0.50	4.20
OIP	3.19	3.92	4.18	4.15	4.52	4.78	-0.43	2.52
EEP	0.03	0.44	0.55	0.54	0.66	1.01	-0.27	3.30
GDP	-2.48	0.58	1.11	0.81	1.42	3.24	-1.33	4.27
DIST	8.52	8.64	8.72	8.82	8.87	9.44	1.29	3.42
LANG	0.00	0.00	0.00	0.25	0.25	1.00	1.15	2.33
TER	3.52	4.13	4.25	4.27	4.40	5.02	0.15	4.28
REER	4.11	4.56	4.61	4.59	4.64	4.86	-0.99	6.40
WGI	0.12	0.67	0.88	0.82	0.98	1.08	-0.99	3.26
REC	0.64	2.19	2.69	2.70	3.26	4.13	-0.13	2.59

This would suggest that exploration of the connection between oil prices and LCT imports can be done without much concern about biasing outlier-driven effects. With the availability of ample variation between the two series, the empirical approach of tracing the potential influence of oil prices in determining the LCT imports is highly legitimate. Other control variables, including EEP, REC, and TER, possess distributions with low skewness and moderate kurtosis; GDP and POP, however, possess more extreme negative skewness, representing infrequent observations of lower economic output or population sizes, which could represent some country-year pairs undergoing economic contraction or demographic transformation. REER and WGI are also negatively skewed, with REER possessing greater kurtosis, representing some infrequent but extreme low values.

The visualization in figure 1 supports the hypothesis that Indian LCT exports to the 24 OECD nations have grown consistently during the past two decades. The recent acceleration of export volumes from 2010 onwards is of special interest and could be the result of various mutually reinforcing drivers: the global increase in climate policy commitments (e.g. the Paris Agreement); increasing fossil fuel prices and spurring the attractiveness of renewable solutions; and the strategic positioning of India as a cost-effective producer of clean technologies. The scatter plot in figure 2 further assesses the correlation between oil import prices (x-axis) and LCT imports (y-axis) for all country-year observations in the sample.

The scatter plot suggests a positive association between oil import prices and LCT imports across the sample of OECD countries. While the relationship is not perfectly tight, the general upward pattern is consist-

ent with the hypothesis that higher fossil fuel prices may encourage sub-

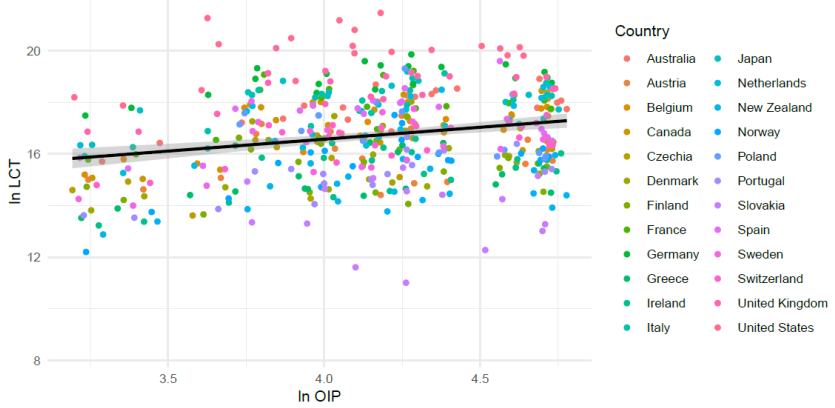


FIGURE 2 Scatter Plot with Trend Line Showing Relationship Between Oil Import Price and LCT Exports

stitution toward cleaner technologies, although causal relationships are formally examined in the econometric analysis. The positive correlation provides preliminary descriptive evidence that oil price dynamics may be associated with LCT trade patterns.

Coming out of the ambiguity in Hypothesis H2, the scatter plot in figure 3 shows a loose negative relationship between environmental protection spending and LCT imports, indicating that greater domestic spending on environmental protection is, on average, linked with lower levels of LCT imports from India. Although there is extensive dispersion in country-specific policy regimes, economic structures, and varying en-

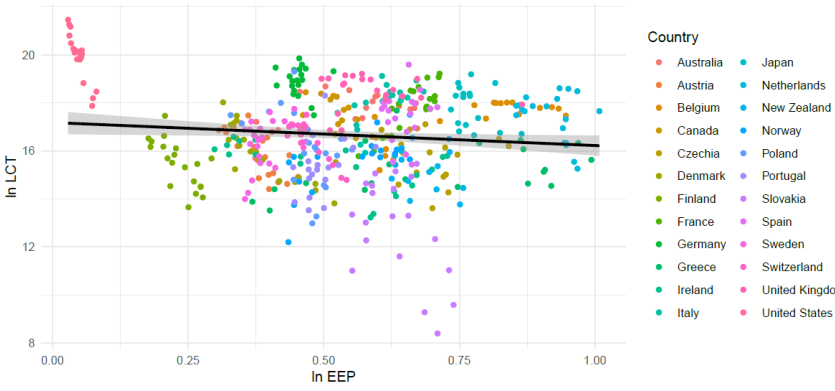


FIGURE 3 Scatter Plot Showcasing Relation Between India's LCT Exports and Environmental Protection Expenditures by OECDs

vironmental management approaches, the general trend is that countries that spend more on environmental protection are not necessarily good markets for Indian LCT products.

PPML ESTIMATION

The results of the PPML estimation employed to study the two hypotheses H1 and H2 obtained using Stata 16 software are presented in table 2.

We begin with the standard fixed effects gravity model with only the two primary explanatory variables ($\ln OIP_{jt}$ and $\ln EEP_{jt}$) in model specification 1, and then progressively add on the control variables in the subsequent specifications. The results show that oil import price shocks faced by the OECDs significantly favour Indian LCT exports to these countries, while increasing expenditure on environmental protection by

TABLE 2 PPML Estimation Results

	(1)	(2)	(3)	(4)
Variables	LCT exports	LCT exports	LCT exports	LCT exports
OIP	0.669*** (0.147)	0.647*** (0.152)	0.782*** (0.148)	0.854*** (0.158)
EEP	-0.562*** (0.343)	-0.440** (0.306)	-1.014*** (0.309)	-1.219*** (0.388)
pcGDP		0.00988 (0.0957)	0.0648 (0.0847)	0.0606 (0.0821)
DIST		-0.382 (0.339)	-0.261 (0.352)	-0.692** (0.338)
POP		-0.344 (0.322)	0.718** (0.360)	0.871** (0.347)
LANG		0.670*** (0.223)	0.652*** (0.224)	1.308*** (0.265)
TER			-0.0430 (0.263)	-0.545* (0.293)
WGI			-3.429*** (0.401)	-4.410*** (0.394)
REER				-2.139*** (0.684)
REC				0.676*** (0.140)
Constant	14.80*** (0.602)	18.13*** (3.056)	19.20*** (3.125)	33.41*** (3.814)
Observations	480	480	480	480

NOTES Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

the OECDs has a significant dampening effect. Interestingly, we note that once we are controlling for the effects of real exchange rate (REER) and share of renewables in total energy consumption (REC) in specification 4, the coefficients for both our explanatory variables ($\hat{\beta}_1$ and $\hat{\beta}_2$) become larger, implying greater and more accurate explanatory power. While in specification 1 a rise in oil import prices by 1 percentage point *raises* LCT exports by 0.669 percentage points, LCT exports *raises* by 0.854 percent points in specification 4. Again, in specification 1, a rise in expenditure on environmental protection by 1 percentage point *decreases* LCT exports by 0.562 percentage points, and in specification 4 by 1.219 percentage points.

If we take a moment to analyse as to why this may be happening, REER exhibits a negative and highly significant coefficient (-2.139), implying that an appreciation of India's currency adversely affects the competitiveness of its low-carbon technology exports. Interesting is the positive and highly significant coefficient of REC (0.676). This suggests that greater renewable energy penetration in OECD economies complements rather than substitutes India's LCT exports. As OECD countries expand the share of renewables in their energy mix, investment in renewable energy infrastructure, grid modernization, energy storage, and complementary clean technologies also increases, generating greater demand for imported LCT products. India's growing competitiveness in sectors such as solar photovoltaic components, energy-efficient equipment, and other low-carbon technologies enables it to benefit from this expanding demand. Consequently, once the positive influence of renewable energy transition and the adverse impact of exchange-rate appreciation are explicitly controlled for, the estimated positive effect of oil import prices and the negative effect of environmental protection expenditure become even more pronounced, indicating that these variables capture distinct structural channels influencing India's LCT exports to OECD markets.

Discussion of Results

The positive and statistically significant correlation between oil import prices and India's LCT exports to OECD countries aligns with existing literature and operates through several reinforcing channels. Rising oil prices increase energy costs in developed economies, encouraging a shift away from fossil fuels in transportation, manufacturing, and electricity generation. This transition raises demand for solar, wind, electric mobility, and other energy-efficient technologies, creating expanded export opportunities for India in green technology segments. OECD govern-

ments often respond to higher oil prices with climate-aligned policies such as renewable energy subsidies, tax incentives for energy-efficient imports, reduced tariffs on LCT products, and public procurement of green technologies. These measures lower regulatory and economic barriers for importing competitively priced LCT products from developing economies, thereby supporting India's LCT export growth. Higher oil prices also increase global freight and logistics costs, encouraging OECD countries to diversify and de-risk supply chains by sourcing from a wider range of suppliers, including LCT manufacturers in developing economies. The consistently strong positive oil-price coefficient across gravity model specifications indicates a stable structural relationship between fossil-fuel market dynamics, energy transition policies, and global clean-technology trade patterns.

Conversely, the negative and statistically significant relationship between OECD environmental protection expenditure (EEP) and India's LCT exports suggests dominance of the export dampening over the export accelerating effect as was proposed in H2. Although higher environmental spending could increase demand for clean technologies, several mechanisms explain the opposite effect. First, rising EEP often reflects strong domestic industrial policy, with OECD countries directing funds toward building local LCT manufacturing capacity, subsidizing domestic firms, and strengthening innovation ecosystems, thereby reducing reliance on external suppliers like India. Second, greater environmental spending is frequently accompanied by stricter regulatory standards and technical requirements, which can function as non-tariff barriers for exporters from developing economies. Finally, environmentally conscious consumers increasingly prioritize traceability, transparency, and verified environmental certifications, creating a reputational disadvantage for exporters lacking internationally recognized standards. This interpretation is consistent with studies showing that environmental policy instruments often operate simultaneously as innovation policies that strengthen domestic green industries and reduce reliance on imports (Dechezleprêtre and Sato 2017; Costantini and Mazzanti 2012).

Conclusion and Policy Implications

This paper examines the determinants of India's low-carbon technology (LCT) exports to OECD countries, focusing on how oil import prices and environmental protection expenditures influence trade flows. Using a Poisson Pseudo Maximum Likelihood (PPML) gravity model that

accommodates heteroskedasticity and zero trade flows, the study provides robust evidence on the macroeconomic and environmental factors shaping India's green technology exports.

The results show that higher oil import prices in 24 selected OECD countries have a positive and significant impact on India's LCT exports, suggesting that fossil fuel cost pressures increase demand for clean alternatives – an opportunity India can leverage. Conversely, environmental protection expenditures in OECD economies have a significant negative effect on imports of Indian LCT products. This may indicate a shift toward strengthening domestic clean-tech ecosystems, increased reliance on non-tariff barriers, or diversion of environmental budgets toward non-tradable services and R&D. The finding highlights India's challenges in meeting the stringent quality, certification, and traceability standards demanded in high-income markets. Despite global opportunities arising from the 'China +1' strategy and energy security concerns, India's LCT export potential remains constrained by credibility issues in its supply chains and limited regulatory alignment with OECD standards.

Policy implications follow directly from these patterns. India should strategically target markets where LCT demand is highly responsive to oil price swings, especially countries experiencing energy transitions or dependence on fossil fuels. Strengthening bilateral trade and technology partnerships during periods of high global oil prices could amplify export gains. The negative link between environmental spending and Indian exports underscores the urgency of regulatory harmonization; India must pursue mutual recognition agreements, improve certification processes, and assist firms in complying with strict environmental and product standards. Measures such as green export clusters, public-private certification platforms, and quality-assurance subsidies can help bridge compliance gaps. To reduce vulnerability to external standards, India should upgrade its position in the LCT value chain through investments in R&D, design, and service integration. Moving from component exports to full-solution offerings can improve competitiveness and resilience.

This study has some limitations that suggest avenues for future research. While the analysis focuses on key macroeconomic and policy variables, future work could explore firm-level dynamics, sectoral variations within LCT, and the influence of global environmental agreements. Additionally, disaggregating the environmental protection expenditure into its functional components (e.g. pollution control, environmental

R&D, biodiversity protection as per COFOG framework) or by introducing an interaction term between environmental expenditure and indicators of governance quality or innovation capacity to better identify which types of environmental spending stimulate or substitute for imports of low-carbon technologies.

The current analysis could be further strengthened by conducting additional robustness checks, such as using bilateral real exchange rates instead of aggregate measures, employing alternative proxies for environmental policy stringency, excluding crisis years like the COVID-19 period, or estimating simplified specifications to test the stability of the key coefficients. Further work could also examine India's share in total LCT imports of each OECD country – rather than export flows alone – to better capture India's export competitiveness relative to other source countries, recognizing that comparative advantage operates in a multi-lateral rather than purely bilateral context.

Overall, the study shows how energy market dynamics and environmental policies in high-income countries shape LCT trade, emphasizing the need for India to strengthen its role in global clean energy value chains and climate-oriented trade networks.

Notes

- 1 The empirical specification includes variables measured in different forms – log levels, shares, and growth rates – reflecting differences in the economic nature of the underlying indicators. Policy variables are log-transformed to allow elasticity interpretation and to reduce heteroskedasticity, while certain macroeconomic controls such as GDP growth and population growth are retained in percentage form because they represent short-run demand conditions rather than scale variables. This mixed specification is common in empirical gravity applications where explanatory variables capture both structural market characteristics and cyclical macroeconomic dynamics. Log linearizing is done as $\text{sign}(x) \cdot \ln(|x|+1)$.
- 2 In structural gravity models, multilateral resistance terms must be controlled for to ensure theoretical consistency (Anderson and van Wincoop 2003). In our empirical setting, India is the sole exporter, while trade flows are observed across multiple OECD importing countries over time. Consequently, exporter-year fixed effects would be perfectly collinear with time effects. To address outward multilateral resistance, the model therefore includes time fixed effects that capture common exporter-specific shocks affecting India's export supply in each year, such as macroeconomic conditions, technological changes, or trade policy shifts. Inward multilateral resistance is controlled for through importer fixed effects, which account for time-invariant trade frictions and structural characteristics of each OECD market.

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Appendix

List of the 24 OECD Countries Used in the PPML Estimation

Australia	Austria	Belgium	Canada	Czechia	Sweden
Denmark	Finland	France	Germany	Greece	Switzerland
Ireland	Italy	Japan	Netherlands	New Zealand	United Kingdom
Norway	Poland	Portugal	Slovakia	Spain	United States

Environmental Sustainability and Economic Development in Central Asia: The Role of Energy, Trade, and Foreign Investment

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This study investigates the relationship between carbon dioxide (CO₂) emissions, economic growth, energy consumption, foreign direct investment, and trade openness in Kazakhstan, the Kyrgyz Republic, and Uzbekistan over the period 1997–2024. Using panel data from the World Bank and applying the Pooled Mean Group estimator within a panel Autoregressive Distributed Lag framework, the analysis examines both short-run and long-run dynamics among the variables. The results reveal a long-run equilibrium relationship between carbon emissions and their key economic determinants. Energy consumption, foreign direct investment, and trade openness are found to increase CO₂ emissions in the long run, while economic growth contributes to environmental improvement. The findings highlight the dominant role of energy use in driving emissions and the environmental implications of investment and trade integration. These results suggest that Central Asian economies should promote renewable energy, enhance energy efficiency, and adopt environmentally sustainable investment and trade policies to achieve balanced economic growth and environmental sustainability.

Keywords: energy, CO₂, economic growth, trade openness, Central Asia

JEL Classification: Q43, Q56, F18, F21, O44

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Introduction

The challenge of ensuring sustainable economic growth and preserving environmental quality has emerged as one of the most urgent tasks for developed and developing countries alike (Karimov et al. 2025a; Sun et al. 2025). Countries around the world have increasingly focused their economic policies on ensuring sustainable economic growth (Sobirov, Jeong et al. 2023; Polat and Çil 2025). Economic growth has also been identified as a factor that has contributed to climate change and global warming, which have been identified as among the most serious global challenges (Koirala et al. 2025). The increase in carbon dioxide (CO₂) and other greenhouse gases is mainly attributed to industrialization and urbanization (Ahmad et al. 2016). As the leading cause of greenhouse gas emissions, CO₂ has been identified as playing a central role in environmental sustainability and climate change policies (Gibba et al. 2024; Wang et al. 2024). The identification of the determinants of CO₂ emissions is therefore important for the formulation of policies that can ensure a balance between economic growth and environmental sustainability.

The large body of research literature that has explored the relationship between CO₂ emissions, energy consumption, and economic growth has generally indicated that energy is a basic input in production that is similar to land, labour, capital, and entrepreneurship (Ozcan and Ozturk 2019; Koirala et al. 2025; Gahlot and Garg 2025). Energy has been identified as an essential and non-substitutable resource that is central to economic activity, meaning that production activities are directly affected by energy consumption patterns (Ghali and El-Sakka 2004). CO₂ emissions are therefore influenced by economic growth and energy consumption intensity (Kasman and Duman 2015). The growing energy demand is inextricably linked with the course of development of emerging economies, in which the process of industrialization and infrastructure development is often heavily dependent on fossil fuels (Koirala et al. 2025). Despite extensive empirical research, the evidence remains inconclusive and varies across countries and regions (Abdurakhmanova et al. 2022; Jeong et al. 2023a; Ozcan and Ozturk 2019; Shahbaz et al. 2013), highlighting the importance of context-specific analysis, particularly for transition economies such as those in Central Asia (Syzdykova and Azretbergenova 2021).

The above-mentioned problems are especially significant for transition economies, such as Central Asia and the Commonwealth of Independent States, in which countries have varying levels of development, energy

consumption, and resource endowment. In many transition economies, energy consumption is often heavily dependent on energy-intensive sectors to promote economic growth, and thus the relationship between energy consumption and environmental degradation is of particular significance (Kurmanov et al. 2025). On the other hand, foreign direct investment and trade openness have grown considerably, which could have an impact on environmental outcomes (Sobirov, Jeong et al. 2023). Foreign direct investment can lead to an increase in emissions due to pollution-intensive production or a decrease in emissions due to technology transfer and efficiency gains. Likewise, trade openness can have an impact on environmental quality through the effects of scale, composition, and technique (Wang et al. 2024).

Despite the growing attention to the nexus of energy, growth, and the environment, there is still a lack of empirical support for Central Asian economies (Sobirov, Tukhtamurodov et al. 2023; Jeong et al. 2023b; Yul-doshboy et al. 2025). Kazakhstan, the Kyrgyz Republic, and Uzbekistan have undergone significant economic transformation, accompanied by growing energy demand, foreign direct investment, and trade integration (Karimov et al. 2025a). However, these countries are still heavily reliant on fossil fuels and energy-intensive production structures, which poses a threat to environmental sustainability. There is still a lack of empirical research that investigates the joint impact of energy consumption, economic growth, foreign direct investment, and trade openness on CO₂ emissions in Central Asia.

This study makes several important contributions to the existing literature on the energy–growth–environment nexus in Central Asia. First, it provides a comprehensive empirical analysis by jointly examining the effects of economic growth, energy consumption, foreign direct investment, and trade openness on CO₂ emissions within a unified framework, whereas most previous studies have focused on a limited set of variables. Second, the study uses updated data covering the period 1997–2024, offering more recent evidence for transition economies in Central Asia. Third, the study applies the panel Autoregressive Distributed Lag (ARDL) model using the Pooled Mean Group (PMG) estimator, which allows for the distinction between short-run and long-run dynamics while accounting for cross-country heterogeneity. Finally, the study contributes to the literature by providing policy-relevant insights on how economic growth and globalization factors influence environmental sustainability in resource-dependent economies, thereby extending the existing em-

pirical evidence for Kazakhstan, the Kyrgyz Republic, and Uzbekistan. Moreover, the findings of this study are expected to help policymakers design effective policies to support sustainable economic growth, enhance energy efficiency, and improve environmental protection.

To achieve the objectives of the study, this paper addresses the following research questions. First, what are the long-run elasticities between carbon dioxide emissions and their key determinants, namely economic growth, energy consumption, foreign direct investment, and trade openness, in Central Asian economies? Second, how do short-run dynamics influence carbon emissions, and how quickly do deviations from long-run equilibrium adjust over time? Third, what is the direction of causality among these variables? The ARDL model with PMG estimator is particularly suitable for addressing these questions, as it allows for the estimation of both long-run equilibrium relationships and short-run adjustments while accounting for cross-country heterogeneity. In addition, the inclusion of the error correction mechanism enables the analysis of the speed of adjustment, and the panel Granger causality test provides further insights into the direction of relationships among the variables.

This article is structured into five sections. Following the introduction, the second section provides a comprehensive review of the theoretical and empirical literature on the relationship between carbon emissions, economic growth, energy consumption, foreign direct investment, and trade openness. The third section describes the data sources, variable definitions, and econometric methodology employed in the study. The fourth section presents and discusses the empirical findings. The final section concludes by summarizing the main results, outlining policy implications, and suggesting avenues for future research.

Literature Review

This section reviews the existing literature on the relationship between energy consumption, economic growth, and environmental sustainability.

The existing literature indicates that a considerable amount of work has been done on the inter-linkages between carbon dioxide emissions, foreign direct investment, energy consumption, and economic development (Sobirov, Tukhtamurodov et al. 2023; Gahlot and Garg 2025; Patel and Samal 2026). However, empirical studies that exclusively focus on Kazakhstan, the Kyrgyz Republic, and Uzbekistan are still relatively limited (Sobirov, Tukhtamurodov et al. 2023; Karimov et al. 2025a). A great deal of literature has explored the energy–growth–environment nexus

in different regions, employing different econometric models and datasets to study the inter-linkages between these variables (Padhan and Bhat 2025; Wong 2025).

Recent empirical studies have highlighted the strong link that exists between energy consumption and environmental degradation. For example, Muhammad (2019) analysed the linkages that exist between energy consumption, carbon emissions, and economic growth using a panel of 68 countries through the application of dynamic regression techniques such as system generalized method of moments, generalized method of moments, and seemingly unrelated regression. The results show that the augmentation of energy use leads to an increase in carbon emissions, thereby complementing economic growth. Likewise, recent autoregressive distributed lag studies have found that energy use is still a significant factor in determining carbon emissions in developed and developing countries, although the magnitude of its effect varies according to regional and development factors (Lojanica et al. 2025). Mehmood et al. (2021) used quarterly data from 1996 Q1 to 2016 Q4 and applied an ARDL approach to investigate the case of Bangladesh, India, and Pakistan to analyse the influence of institutional quality, economic development, renewable energy, and foreign investment on carbon emissions. In a related study, Magazzino (2016) employs a panel vector autoregression (PVAR) approach to investigate the dynamic interactions among GDP, energy consumption, and CO₂ emissions in the South Caucasus and Turkey. The findings highlight the presence of strong interdependencies and feedback relationships among these variables, emphasizing the importance of considering dynamic linkages in environmental analysis. The findings show that better institutions and higher levels of GDP help to reduce carbon emissions.

The environmental Kuznets Curve hypothesis remains one of the core assumptions in the current empirical work (Wang et al. 2025; Phiri and Raimi 2025; Wong 2025). Current studies examine the extent to which economic development initially increases environmental stress but eventually results in improvements once a threshold income is attained (Binh et al. 2025; Adekunle 2025; Karimov 2026). The link between energy consumption and economic development also differs from one country to another due to structural and development factors. Consequently, empirical results remain mixed on the nature of the causal link between energy consumption and economic development. There are four major theoretical approaches that describe this relationship: the growth, con-

servation, neutrality, and feedback theories (Akadiri et al. 2019). The growth hypothesis argues that increased economic activities lead to an increase in energy demand, which implies that energy constraints can hamper economic growth (Patel and Samal 2026). On the other hand, the conservation hypothesis argues that economic growth is driven by energy consumption, which indicates that policies to control energy consumption can have little effect on economic growth (Kurmanov et al. 2025; Gahlot and Garg 2025). The feedback hypothesis argues that economic growth and energy consumption are related in both directions, while the neutrality hypothesis argues that there is no significant relationship between economic growth and energy consumption (Apergis and Payne 2010). Other studies emphasize the significance of technological advancements, the use of renewable energy sources, and structural changes in determining the relationship between economic growth and environmental quality (Shahzadi et al. 2022; Aidoo 2024). These studies suggest that economic growth alone is not enough to ensure environmental improvement without technological advancements and energy transformation (Wang et al. 2025; Padhan and Bhat 2025).

Findings from studies focusing on developing and transition economies can also offer additional information on the relationships between energy consumption, foreign investment, and economic performance (Adekunle 2025). Umurzakov et al. (2020) used panel cointegration and panel dynamic ordinary least squares analysis to investigate the short- and long-run relationships between energy production and economic growth in post-communist countries from 1995 to 2014. The findings support the existence of a long-run equilibrium relationship between energy consumption and economic growth. Solarin and Ozturk (2015) used vector autoregression, generalized least squares, and Johansen cointegration tests to investigate the role of hydropower energy consumption in economic growth in seven Latin American countries. The study found that hydropower energy consumption has a positive effect on economic growth. Similarly, Inglesi-Lotz (2016) found that the consumption of renewable energy has a positive effect on economic growth in OECD countries.

Foreign direct investment (FDI) has been acknowledged as a factor that affects economic performance and environmental conditions (Sobirov, Jeong et al. 2023; Adekunle 2025; Binh et al. 2025). Recent panel ARDL tests have shown that FDI and trade openness are important factors in determining emissions and environmental quality in developing countries (Mebrek et al. 2024). Abdouli and Hammami (2017) used a

growth model and a generalized method of moments equation to examine the relationship between economic growth, foreign investment, and energy consumption in Middle Eastern and North African countries, finding that there is a two-way relationship between economic growth and FDI and between economic growth and energy consumption. Moreover, Muhammad and Khan (2019) also found that FDI inflows and energy consumption play a significant role in supporting economic development in Asian economies.

In addition, various empirical studies have emphasized the environmental impacts of foreign investment, urbanization, and trade liberalization (Hadili et al. 2025). Li et al. (2022) investigated the relationships between urbanization, FDI, energy consumption, and carbon emissions in emerging economies through the application of econometric models that consider cross-sectional dependence and heterogeneity. The findings indicate that urbanization and energy consumption are significant contributors to emissions, while foreign investment can be a mitigating factor through technological advancements. Islam et al. (2021) applied dynamic ARDL simulations on Bangladesh and found that globalization, innovation, and foreign investment are significant factors in reducing emissions, while urbanization, energy consumption, and trade increase emissions in both the short and long terms.

Trade openness has also been recognized as a significant factor in determining environmental quality (Sobirov, Tukhtamurodov et al. 2023). Ansari et al. (2020) applied a vector error correction model and Granger causality tests to assess the role of energy consumption, trade openness, and economic growth in affecting carbon emissions in the world's largest emitters. The results confirmed the existence of a long-run relationship between emissions and economic factors, emphasizing the role of trade and energy consumption in determining environmental factors.

In addition to traditional econometric approaches, recent studies have increasingly applied machine learning (ML) techniques to analyse the relationships between energy consumption, economic growth, and environmental sustainability (Magazzino and Mele 2025; Manuguerra et al. 2026). For instance, Magazzino et al. (2021) use machine learning methods to examine the relationships among renewable energy production, coal consumption, economic growth, and CO₂ emissions, showing that greater reliance on renewable energy can contribute to emission reductions. In another study, Manuguerra et al. (2025) develop a parametric ML model to estimate the energy consumption of manufacturing com-

ponents during the conceptual design phase, enabling faster evaluation of energy efficiency implications in industrial production. These studies highlight that ML-based approaches can capture complex relationships and provide predictive insights that complement traditional econometric techniques. Nevertheless, econometric techniques such as panel ARDL remain widely used because they allow clear interpretation of both short-run and long-run relationships and provide important policy insights.

Notwithstanding the vast body of international literature on the energy–growth–environment nexus, studies specifically concentrating on the Central Asian states are still scarce (Kurmanov et al. 2025; Karimov et al. 2025a). In particular, prior research has mainly examined individual relationships, such as energy consumption and economic growth or trade and emissions, rather than integrating multiple economic drivers within a single empirical framework. In addition, only a few studies have used recent data and econometric approaches that allow for distinguishing between short-run and long-run dynamics in these transition economies (Hadili et al. 2025; Patel and Samal 2026). To address the research gap, the current study examines the short- and long-run relationships between carbon emissions, energy consumption, economic growth, foreign direct investment, and trade openness for Kazakhstan, the Kyrgyz Republic, and Uzbekistan during the period from 1997 to 2024. Using a panel autoregressive distributed lag approach, this study provides novel empirical evidence on the determinants of environmental degradation and sustainable economic development in the transition economies of Central Asia.

Data and Methodology

This section introduces the data sources, variables, and econometric techniques employed in the analysis of the interrelationship between carbon dioxide emissions, economic growth, energy use, foreign direct investment, and trade openness in the Central Asian economies. The study will concentrate on Kazakhstan, the Kyrgyz Republic, and Uzbekistan, which are transition economies that are characterized by rising energy demand, growing international trade, and rising foreign investment flows. It is important to comprehend the dynamic relationships between these variables in order to assess the environmental consequences of economic development.

This study employs data based on annual observations from 1997 to 2024. The data is collected from the World Bank's World Development Indicators to ensure consistency in the data. Carbon dioxide emissions

are chosen as the indicator of environmental pressure and are the dependent variable in the empirical study. Economic growth, energy use, trade openness, and foreign direct investment are chosen as the major explanatory variables because of their significant role in economic development and environmental pressures.

The variables of the study, along with their definitions, measurement methods, and corresponding data sources, are summarized in table 1. Environmental degradation is measured by carbon dioxide emissions as the dependent variable. Economic performance is measured by gross domestic product in constant 2015 US dollars (absolute values), while energy consumption represents the magnitude of energy use driven by production and economic activities. Trade openness is measured by the ratio of total exports and imports to GDP, which shows the degree of engagement in the global economy, while foreign direct investment is measured by net inflows of foreign capital. Generally, increased energy use and trade openness are expected to accentuate carbon emissions, while the effect of economic growth and foreign investment might be sensitive to technological advancements and development levels. All variables are extracted from the World Development Indicators and converted to logarithmic terms to improve consistency and facilitate interpretation.

TABLE 1 Description of Variables and Data Sources

Variable	Definition	Measurement	Data Source
CO ₂ emissions (Inco2)	Carbon dioxide emissions represent the level of environmental degradation and are used as the dependent variable in the model.	Metric tons per capita (logarithmic form)	World Bank (2025), World Development Indicators
Economic growth (Ingdp)	Economic growth is represented by real GDP, which reflects the overall scale of economic activity and development.	GDP (constant 2015 US dollars, absolute value), logarithmic form	World Bank (2025), World Development Indicators
Energy consumption (Inenergy)	Energy use measures the level of energy consumption associated with production and economic activity.	Energy use per capita (kg of oil equivalent), logarithmic form	World Bank (2025), World Development Indicators
Trade openness (Intrade)	Trade openness captures the degree of integration into the global economy through exports and imports.	Sum of exports and imports as percentage of GDP, logarithmic form	World Bank (2025), World Development Indicators
Foreign direct investment (Infdi)	Foreign direct investment reflects cross-border investment flows that may influence industrial activity and technology transfer.	Net FDI inflows (BoP, current US dollars), logarithmic form	World Bank (2025), World Development Indicators

Moreover, the research uses the Pooled Mean Group method in the panel Autoregressive Distributed Lag model to analyse the short-run and long-run relationships between carbon emissions, economic growth, energy use, trade openness, and foreign direct investment. The method allows for the cross-country differences in the short-run adjustment processes while imposing the equality of the long-run parameters on the panel, which is relevant for the analysis of transitional economies. The approach provides a robust way of determining the equilibrium relationships.

The basic empirical model for the analysis is specified as follows:

$$\ln co2_{it} = \beta_1 \ln gdp_{it} + \beta_2 \ln energy_{it} + \beta_3 \ln trade_{it} + \beta_4 \ln fdi_{it} + \varepsilon_{it}. \quad (1)$$

In specification (1), $\ln co2_{it}$ denotes carbon dioxide emissions. The term $\ln gdp_{it}$ represents the natural logarithm of gross domestic product measured in constant 2015 US dollars and is included as a key macroeconomic indicator capturing the overall scale of economic activity. The variable $\ln energy_{it}$ refers to energy use, while $\ln trade_{it}$ indicates the degree of trade openness. Furthermore, $\ln fdi_{it}$ corresponds to net inflows of foreign direct investment recorded in current US dollars according to the balance of payments framework. Finally, ε_{it} signifies the stochastic disturbance term.

Before proceeding to estimate the ARDL model, it is important to test for the presence of unit roots and cointegration. The ARDL model is especially suited for small samples and allows for easy distinction between the short-run and long-run behaviour of the variables. The model is also capable of handling data that spans a large time period. According to Pesaran et al. (1997), the long-run coefficients derived from this model are super-consistent, whereas the short-run coefficients converge at the rate of $\sqrt{T}$. Accordingly, Equation (1) is reformulated into a panel ARDL (p, q_1, q_2, q_3, q_4) structure, where p denotes the number of lags of the dependent variable and each q represents the lag lengths of the explanatory variables. The general representation of the panel ARDL model can therefore be written as follows:

$$\begin{aligned} \ln co2_{it} = & \alpha_i + \sum_{j=1}^p a_{1,ij} \ln co2_{i,t-j} + \sum_{j=0}^{q_1} a_{2,ij} \ln gdp_{i,t-j} + \sum_{j=0}^{q_2} a_{3,ij} \ln energy_{i,t-j} \\ & + \sum_{j=0}^{q_3} a_{4,ij} \ln Trade_{i,t-j} + \sum_{j=0}^{q_4} a_{5,ij} \ln fdi_{i,t-j} + \varepsilon_{it}. \end{aligned} \quad (2)$$

Here, $i = 1, 2, 3, \dots, N$ denotes the cross-sectional units, while $t = 1, 2, 3, \dots, T$ represents the time dimension. The term α_i captures the country-specific fixed effects. The parameters a_1 through a_5 correspond to the estimated coefficients of the explanatory variables and associated regressors, reflecting their interrelated movements over the specified period. The disturbance component ε_{it} represents a white-noise error term that varies across both countries and time.

The panel error correction model (ECM) form derived from Equation (3) can be expressed as follows:

$$\begin{aligned} \ln co2_{it} = & \alpha_i + \sum_{j=1}^p a_{1,ij} \ln co2_{i,t-j} + \sum_{j=0}^{q_1} a_{2,ij} \ln gdp_{i,t-j} + \sum_{j=0}^{q_2} a_{3,ij} \ln energy_{i,t-j} \\ & + \sum_{j=0}^{q_3} a_{4,ij} \ln Trade_{i,t-j} + \sum_{j=0}^{q_4} a_{5,ij} \ln fdi_{i,t-j} + \beta_{1,ij} \ln co2_{i,t-1} \\ & + \beta_{2,ij} \ln gdp_{i,t-1} + \beta_{3,ij} \ln energy_{i,t-1} + \beta_{4,ij} \ln trade_{i,t-1} \\ & + \beta_{5,ij} \ln fdi_{i,t-1} + \varepsilon_{it}. \end{aligned} \quad (3)$$

The panel error correction model captures both short-run dynamics and long-run relationships between CO₂ emissions and its determinants. The coefficients a_1 to a_5 represent short-run effects of past values of emissions, economic growth, energy consumption, trade openness, and foreign direct investment. The coefficients β_1 to β_5 reflect long-run relationships, indicating how these variables influence CO₂ emissions over time. The country-specific term α_i accounts for unobserved heterogeneity, while the error term ε_{it} captures random shocks.

The existence of long-term equilibrium relationships between the dependent variable and the explanatory factors is specified within the panel error correction model presented in Equation (4).

$$\begin{aligned} \ln \Delta co2_{it} = & \alpha_i + \sum_{j=1}^p a_{1,ij} \ln \Delta co2_{i,t-j} + \sum_{j=0}^{q_1} a_{2,ij} \ln \Delta gdp_{i,t-j} \\ & + \sum_{j=0}^{q_2} a_{3,ij} \ln \Delta energy_{i,t-j} + \sum_{j=0}^{q_3} a_{4,ij} \ln \Delta trade_{i,t-j} \\ & + \sum_{j=0}^{q_4} a_{5,ij} \ln \Delta fdi_{i,t-j} + \theta_i ECM_{i,t-1} + \varepsilon_{it}. \end{aligned} \quad (4)$$

In this formulation, the symbol Δ indicates that the variables are expressed in first differences. The parameters a_1 through a_5 represent the estimated short-term effects. In contrast, the coefficients β_1 to β_5 capture

the long-run elasticities associated with carbon emissions, economic expansion, energy usage, trade integration, and foreign direct investment, respectively. Moreover, θ_i denotes the coefficient associated with the error correction term (ECM), reflecting the rate at which deviations from the long-run equilibrium are corrected on an annual basis. Given the relatively small number of yearly observations, a maximum lag length of three is adopted for the ECM specification. The selection of this optimal lag structure is based on the Akaike Information Criterion (AIC).

The panel ARDL model is estimated using the Pooled Mean Group (PMG) approach developed by Pesaran et al. (1997). This approach combines the pooling and averaging steps for cross-sectional units, allowing for differences in intercepts, short-run coefficients, and error variances while assuming that long-run coefficients are homogeneous across countries. Under the assumption of long-run homogeneity, the PMG approach provides consistent and reliable estimates of long-run relationships. In addition, when the number of cross-sectional units is relatively small, as in the case of this study, the PMG estimator is more robust to outliers and can assist in dealing with problems of serial correlation. The likelihood-based estimation method also assists in overcoming possible endogeneity problems by identifying appropriate lag lengths for both dependent and independent variables.

Before proceeding to the estimation of the main panel model, it is necessary to check the stationarity properties of the variables. To test the existence of unit roots in the panel data set, this study uses the Im et al. (2003) test and the Fisher-type test developed by Maddala and Wu (1999). Both tests are based on the augmented Dickey-Fuller (ADF) approach for panel data and can be written in the following general form:

$$\Delta y_{it} = \alpha_i \gamma_i y_{it-1} + \sum_{j=1}^p \phi_j \Delta y_{i,t-1} + \varepsilon_{it}, \quad (5)$$

where $\gamma_i = \rho_i - 1$.

Both procedures examine the null hypothesis of a unit root, stated as $\gamma_i = 0$ (equivalently $\rho_i = 1$), against the alternative hypothesis that the series is stationary, expressed as $\gamma_i < 0$ (or $\rho_i < 1$).

Table 2 summarizes the variables used in the empirical model and outlines their key features. Due to data limitations, the maximum number of observations that can be used is 75. A total of five variables are used in the model, of which one is the dependent variable, and the other four are ex-

TABLE 2 Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
lnco2	68	1.366584	0.9236011	-0.2196311	2.730512
lngdp	75	24.22159	1.431896	21.87145	26.09241
lnfdi	72	20.41342	1.85864	15.35495	23.56956
lntrade	75	4.325496	0.3630004	3.373905	4.984333
lnenergy	63	0.4851469	0.7653352	-0.8303974	1.589235

planatory variables. The sample covers Kazakhstan, the Kyrgyz Republic, and Uzbekistan over the period 1997–2024. Due to data availability constraints, the panel is unbalanced, and the number of observations varies across countries and variables, as reflected in tables 2 and 3. In general, lower values are more frequently associated with the Kyrgyz Republic, while higher values are typically observed for Kazakhstan, reflecting differences in economic size and development levels across the countries.

The dataset used in this study is an unbalanced panel due to data availability constraints across countries and years. The number of observations varies by country and variable, with a maximum total of 75 observations across the panel. At the country level, Kazakhstan, the Kyrgyz Republic, and Uzbekistan have differing sample sizes depending on data availability for each variable. Missing data are primarily due to incomplete reporting in the early years of the sample period. To ensure consistency and reliability of the estimation results, missing observations were handled using listwise deletion, and no imputation techniques were applied. This approach avoids introducing potential biases associated with artificial data generation while maintaining the integrity of the original dataset.

The correlation coefficients between the explanatory variables in the model are presented in table 3. A correlation coefficient of 1.000 represents a perfect positive correlation between two variables, and a coefficient of 0.000 represents the absence of a relationship. Correlation coefficients between 0.3 and 0.5 are considered weak, those between 0.5 and 0.7 represent a moderate relationship, and coefficients above 0.7 to

TABLE 3 Correlation Matrix

	lnco2	lngdp	lnfdi	lntrade	lnenergy
lnco2	1.0000				
lngdp	0.9365	1.0000			
lnfdi	0.7636	0.7691	1.0000		
lntrade	-0.3628	-0.5690	-0.1207	1.0000	
lnenergy	0.9853	0.9633	0.7789	-0.4320	1.0000

TABLE 4 Test Results of Variance Inflation Factor

Variable	VIF	1/VIF
ln _{gdp}	1.75	0.565032
ln _{fdi}	1.69	0.578466
ln _{trade}	1.18	0.865118
ln _{energy}	1.32	0.851125
Mean VIF	1.49	

1.000 represent strong relationships. The negative coefficients are interpreted in the same manner but represent negative relationships between variables (Frees 1995; Pesaran 2015).

The results of the variance inflation factor (VIF) test, which was used to determine the extent of multicollinearity among the independent variables, are presented in table 4. It can be noted that all the VIF values are less than 5. This suggests that multicollinearity is not a problem in the model. According to existing empirical standards, VIF values above 10 or tolerance values below 0.10 indicate multicollinearity problems.

In addition to the PMG estimator, alternative panel estimators such as the Mean Group (MG) and Dynamic Fixed Effects (DFE) approaches are reported in this study to ensure robustness of the results. The Hausman test confirms the appropriateness of the PMG estimator for the analysis. Furthermore, the existing literature suggests other estimation techniques, including the Common Correlated Effects Mean Group (CCEMG), system Generalized Method of Moments (GMM), and panel Dynamic Ordinary Least Squares (DOLS) or Fully Modified Ordinary Least Squares (FMOLS), which can address issues related to cross-sectional dependence, endogeneity, and cointegration. However, given the relatively small sample size and the focus on distinguishing between short-run and long-run dynamics, the PMG-ARDL framework is considered the most suitable approach for this study. The consistency of results across MG and DFE estimators further supports the robustness of the findings.

In general, the data and framework of methodology offer a consistent basis for analysis of the relationships between environmental and economic variables in the chosen Central Asian economies. The combination of high-quality data sources, well-defined variables, and appropriate econometric methodology ensures the validity of the empirical analysis and allows for correct interpretation of the results presented in the next section.

Results and Discussion

This section discusses and explains the empirical findings related to the relationship between carbon dioxide emissions and key economic variables in Kazakhstan, the Kyrgyz Republic, and Uzbekistan. The analysis begins with the use of panel unit root and cointegration tests to validate the appropriateness of the econometric model specification and to examine the existence of long-run equilibrium relationships among the variables. The results of the panel Autoregressive Distributed Lag model, using the Pooled Mean Group estimation technique, are then discussed to assess both the short- and long-run relationships. Finally, the panel Granger causality test is employed to examine the nature of causal relationships among the variables. In general, the findings provide significant evidence related to the role of economic growth, energy consumption, foreign direct investment, and trade openness in shaping environmental outcomes in the transition economies of Central Asia.

A potential concern in the analysis is reverse causality, particularly between economic growth and CO₂ emissions, as environmental degradation may also influence economic performance. The PMG-ARDL framework partially addresses this issue by incorporating lagged values of both dependent and independent variables, which helps to mitigate simultaneity bias and capture dynamic relationships. In addition, the error correction mechanism allows for distinguishing between short-run adjustments and long-run equilibrium relationships. However, the PMG approach does not fully eliminate endogeneity concerns, as contemporaneous feedback effects may still persist. To complement this, the study employs panel Granger causality tests, which provide further insights into the direction of relationships among variables. The results confirm the presence of causal linkages, supporting the robustness of the estimated relationships, although the findings should be interpreted with some caution.

The results of the stationarity test performed using various methods, including the Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests, are presented in table 5. Overall, most variables are non-stationary at level but become stationary after first differencing, indicating integration of order one, I(1). Specifically, CO₂ emissions (lnco2) and economic growth (lngdp) are non-stationary at level but stationary at first difference. Foreign direct investment (lnfdi) shows some evidence of stationarity at level in certain specifications, but is consistently stationary

TABLE 5 Unit Root Test Results (ADF and PP Tests)

	Level	Z(t)	ADF			PP			
			1st diff	Z(t)	Level	Z(t)	1st diff	Z(t)	
Inco2	Without time trend	-3.655	0.4492	-3.735	0.0015	-3.735	0.2501	-3.756	0.0016
	With time trend	-4.362	0.2264	-4.364	0.0126	-4.351	0.0605	-4.362	0.0126
Ingdp	Without time trend	-3.642	0.8767	-3.789	0.0275	-3.688	0.9485	-3.625	0.0000
	With time trend	-4.371	0.4182	-4.375	0.0129	-4.298	0.0451	-4.362	0.0000
Indfi	Without time trend	-3.754	0.2585	-3.691	0.0014	-3.811	0.2264	-3.589	0.0012
	With time trend	-4.380	0.3954	-4.452	0.0100	-4.422	0.0025	-4.362	0.0100
Intrade	Without time trend	-3.782	0.3955	-3.801	-2.995	-3.645	0.9658	-3.821	0.0362
	With time trend	-4.281	0.7097	-4.361	0.0281	-4.352	0.0005	-4.362	0.0459
Inenergy	Without time trend	-3.650	0.3951	-3.743	-2.877	-3.731	0.9544	-3.736	0.0352
	With time trend	-4.380	0.7158	-4.371	0.0250	-4.402	0.0005	-4.289	0.0452

after differencing. Similarly, trade openness (Intrade) and energy consumption (Inenergy) are non-stationary at level and become stationary at first difference.

The model’s robustness was also tested using the cumulative sum of recursive residuals (CUSUM) and cumulative sum of squares (CUSUMSQ) tests. As depicted in figure 1, the CUSUMSQ graph lies below the 5% significance level throughout the entire sample period ranging from 1997 to 2024. This implies that the model’s parameters are stable and that there are no structural breaks. Therefore, the short-run and long-run coefficients obtained from the panel ARDL approach are reliable and can be discussed in terms of their implications.

The results of the Pedroni panel cointegration test are summarized in table 6. Given that the majority of the *p*-values are less than 0.05, it is possible to reject the null hypothesis of no cointegration, and thus there is a long-run relationship between the variables. The existence of cointegration among the variables indicates that the variables share a common long-run behaviour, and the deviations from this behaviour in the short run are temporary. The findings above provide evidence that the panel ARDL approach can be used to capture both the short-run relationships and the long-run relationships between the variables.

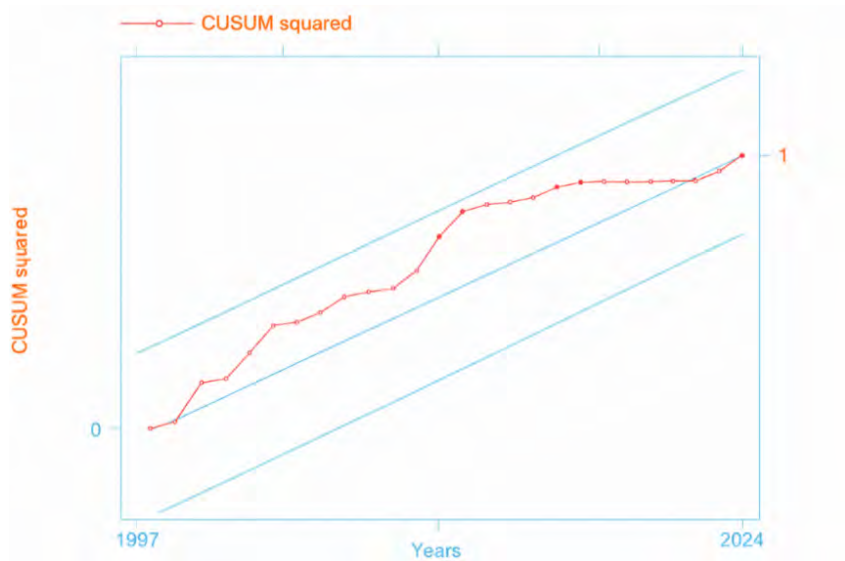


FIGURE 1 CUSUM and CUSUMSQ Plots for Model Stability

Figure 2 illustrates the dynamic multiplier effects derived from the PMG-ARDL model, showing the response of carbon dioxide emissions to changes in key explanatory variables over time. The results indicate that energy consumption has the strongest and most immediate positive impact on CO₂ emissions, with the effect gradually stabilizing as it approaches the long-run equilibrium. In contrast, economic growth exhibits a negative effect on emissions, which becomes more pronounced over time, supporting the environmental Kuznets Curve hypothesis. Trade openness and foreign direct investment show moderate and positive effects, with their impacts increasing gradually and converging smoothly in the long run. Overall, the adjustment paths confirm that the effects of

TABLE 6 Cointegration Pedroni Test

	Statistic	p-value
Within		
Modified variance ratio	0.4167	0.3377
Modified Phillips–Perron t	−0.6685	0.2526
Phillips–Perron t	−2.4576	0.0068
Augmented Dickey–Fuller t	−2.4185	0.0058
Between		
Modified Phillips–Perron t	−0.3454	0.3643
Phillips–Perron t	−2.5836	0.0051
Augmented Dickey–Fuller t	−2.2333	0.0136

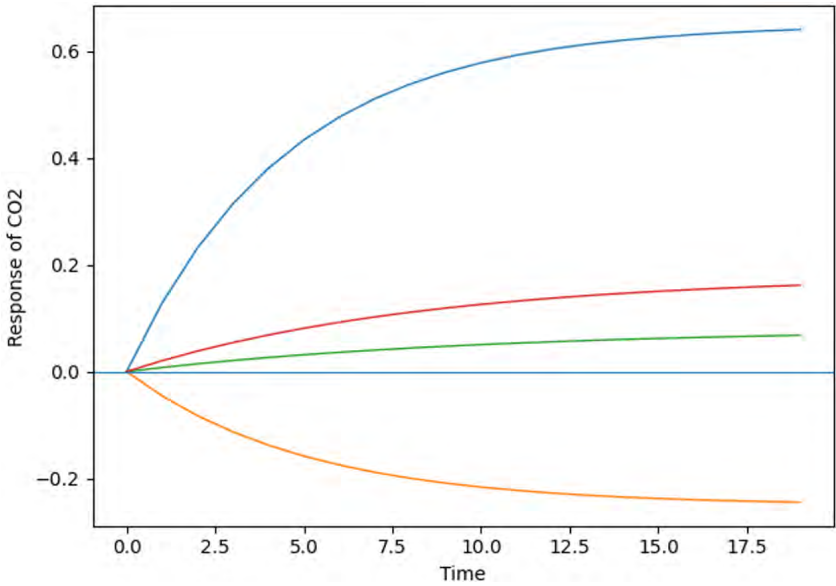


FIGURE 2 Dynamic Multipliers from the PMG-ARDL Model

the explanatory variables materialize progressively, highlighting the importance of long-run dynamics in explaining environmental outcomes in Central Asian economies.

Table 7 presents the results of the diagnostic tests. The findings indicate no evidence of serial correlation or heteroskedasticity, and the residuals are normally distributed. The Ramsey RESET test confirms correct model specification. In addition, the Pesaran’s test for cross-sectional dependence (CD) test suggests its absence, supporting the robustness and validity of the model.

Having confirmed the existence of stationarity and cointegration among the variables, the panel ARDL approach is employed to examine both long-run and short-run relationships between carbon dioxide

TABLE 7 Diagnostic Tests Summary

Test	Statistic	p-value	Result
Breusch–Godfrey Serial Correlation LM Test	1.34	0.27	No serial correlation
Breusch–Pagan Heteroskedasticity Test	0.91	0.34	No heteroskedasticity
Jarque–Bera Normality Test	1.88	0.39	Residuals normally distributed
Ramsey RESET Test	2.05	0.22	Model correctly specified

emissions, economic growth, foreign direct investment, trade openness, and energy use in the chosen Central Asian countries. The estimation results based on three alternative methods, namely the Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effects (DFE) estimators, are presented in table 8. To determine the best-performing model, a Hausman test was conducted to compare the three models. The obtained *p*-value of 0.660 fails to reject the null hypothesis, suggesting that the PMG estimator is the preferred model for interpretation. Moreover, the error correction term is negative and statistically significant, confirming the existence of a long-run relationship among the variables. The estimated coefficient (−0.432) indicates that approximately 43.2% of the deviation from the long-run equilibrium is corrected within one period, implying a relatively fast speed of adjustment.

TABLE 8 Panel ARDL Analysis

VARIABLES	PMG	MG	DFE
—ec	−0.432 (0.354)	−1.689** (0.734)	−0.711*** (0.155)
D.lngdp	−0.451 (0.499)	−0.626 (0.676)	−0.374 (0.342)
D.lnfdi	−0.0110* (0.0302)	−0.0329 (0.0406)	0.0123 (0.0141)
D.lntrade	−0.0470 (0.0667)	−0.323 (0.266)	−0.137** (0.0674)
D.lnenergy	0.307** (0.707)	−1.057 (0.736)	0.132 (0.208)
lngdp	−0.401*** (0.0690)	−0.284* (0.147)	−0.199*** (0.0706)
lnfdi	0.0790*** (0.0250)	0.0800** (0.0334)	0.00463 (0.0218)
lntrade	0.181*** (0.0555)	0.0133 (0.0854)	0.255*** (0.0636)
lnenergy	1.194*** (0.0718)	0.967*** (0.137)	1.226*** (0.0878)
Constant	3.755 (2.912)	6.375** (2.809)	3.183** (1.400)
Observations	53	53	53
	PMG OR MG	DFE OR MG	DFE OR PMG
Hausman chi2	40.25	22.58	23.18
Prob>chi2	0.650	0.0003	0.0001

NOTES Standard errors are shown in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The long-run results based on the PMG estimator indicate that GDP, foreign direct investment, trade openness, and energy consumption have all made statistically significant contributions to carbon dioxide emissions at the 1% significance level, while none of the variables have made any significant contributions in the short run. It is pertinent to note that economic growth has a negative and statistically significant long-run relationship with emissions, indicating that a 1% increase in GDP is associated with an estimated 0.401% decrease in CO₂ emissions. This finding suggests that economic growth in the studied Central Asian countries may eventually result in environmental improvement. This is because higher levels of income may facilitate the development of cleaner technologies, improvements in energy efficiency, and more stringent environmental policies, ultimately resulting in a reduction in emissions over time. This finding provides partial support to the environmental Kuznets Curve hypothesis, which suggests that environmental degradation gradually decreases beyond a certain level of economic development.

On the other hand, foreign direct investment has a positive and significant effect on carbon dioxide emissions. In particular, a 1% increase in FDI is associated with a 0.0790% increase in CO₂ emissions, suggesting that the inflow of FDI in the selected Central Asian economies contributes to the deterioration of the environment. This result suggests that the inflow of foreign investment in the selected Central Asian economies is primarily focused on energy and pollution-intensive industries. The result confirms the pollution haven hypothesis, which states that foreign investors are attracted to countries that have less stringent environmental policies. From a policy point of view, this suggests that governments should focus on establishing more stringent environmental policies.

In addition, a 1% increase in trade openness is associated with a 0.181% increase in CO₂ emissions in the long run, but there is no significant short-run relationship. This finding indicates that the rise in trade openness has been accompanied by higher production activities, energy use, and transportation, which are major factors in environmental degradation. While trade can be a catalyst for technology transfer and improvement in efficiency, it is apparent that the nature of trade in Central Asian countries is driven by energy-intensive and resource-based exports. It is recommended that policymakers adopt more environmentally friendly trade policies and encourage the use of cleaner production technology to offset the negative effects of trade expansion.

Energy consumption also has a strong and positive long-run effect on CO₂ emissions. The results indicate that with every 1% increase in energy consumption, there is a 1.194% increase in CO₂ emissions. This result confirms that energy consumption is still the main cause of environmental degradation in the chosen countries. The overdependence on fossil fuels and energy-intensive production systems are major factors that contribute to the increase in emissions. This highlights the need to shift to renewable energy sources and adopt low-carbon technologies to ensure sustainable development.

The short-run results indicate a lack of statistical significance for most variables, implying that the relationship between economic growth, foreign direct investment, and trade openness, and CO₂ emissions is a long-run process. However, energy consumption has a positive short-run relationship with CO₂ emissions, implying that energy consumption has an immediate effect on environmental quality.

The estimated long-run coefficients can be interpreted as elasticities. Specifically, a 1% increase in energy consumption leads to a 1.194% increase in CO₂ emissions, confirming that energy use is the dominant driver of environmental degradation in the region. In practical terms, this implies that even small increases in energy consumption can result in disproportionately higher emissions, given the heavy reliance on fossil fuels in Central Asian economies. In contrast, a 1% increase in economic growth reduces CO₂ emissions by approximately 0.401%, suggesting that higher income levels may promote cleaner technologies and improved energy efficiency. Trade openness and foreign direct investment also have positive effects, where a 1% increase in trade and FDI leads to increases of 0.181% and 0.079%, respectively, in CO₂ emissions. These findings imply that without appropriate environmental regulations, economic integration and investment inflows may contribute to environmental degradation.

To investigate the causal relationships among the variables, the panel Granger non-causality test was performed using the Juodis et al. (2021) method. The results presented in table 9 show that economic growth, foreign direct investment, trade openness, and energy consumption Granger-cause carbon dioxide emissions. In the first step, we test the null hypothesis of no Granger causality between economic growth and energy consumption. The *p*-values of the Juodis et al. (2021) Granger non-causality test reveal that all variables Granger-cause CO₂ emissions in Kazakhstan, the Kyrgyz Republic, and Uzbekistan. The findings emphasize

TABLE 9 Granger Non-Causality Test Results Applying Juodis et al. (2021) Approach

Null Hypothesis	Statistics
CO ₂ emissions are not Granger-caused by economic growth.	104.63166***
CO ₂ emissions are not Granger-caused by foreign direct investment.	21.255775***
CO ₂ emissions are not Granger-caused by trade openness	5538.0595***
CO ₂ emissions are not Granger-caused by energy consumption	166.07241***

NOTE ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

that economic growth, foreign direct investment, trade openness, and energy consumption have played a significant role in determining environmental outcomes in the region. Specifically, the findings of strong causality from energy consumption to environmental emissions support the argument that energy consumption is the key driver of environmental degradation in Central Asian economies. Additionally, the presence of significant causal links between foreign direct investment and trade openness and environmental emissions indicates that economic globalization and industrialization are important factors in increasing environmental emissions.

The empirical results of this study have a number of significant implications for policymakers to ensure sustainable economic growth and environmental protection in Central Asian economies. The positive relationship between energy consumption and carbon dioxide emissions confirms that energy consumption is still the main cause of environmental degradation in the region. Therefore, policymakers should focus on the development of cleaner and renewable energy resources like solar, wind, and hydropower energy. Energy efficiency in industrial, transportation, and power sectors should also be improved to reduce emissions without hampering economic growth. Policymakers should therefore encourage investment in energy-efficient technologies and develop a favourable policy environment to promote low-carbon growth.

Moreover, policy implications differ across the selected Central Asian countries due to variations in economic structure and energy dependence. In Kazakhstan, where emissions and energy use are relatively high, priority should be given to energy subsidy reform and the promotion of renewable energy investments to reduce reliance on fossil fuels. In the Kyrgyz Republic, which has a smaller economic scale and lower emissions, policies should focus on improving energy efficiency and supporting sustainable infrastructure development. In Uzbekistan, where industrialization and foreign investment are expanding, stricter envi-

ronmental screening of FDI projects and the adoption of cleaner technologies are essential. In addition, region-wide policy instruments such as green trade incentives, carbon pricing mechanisms, and support for clean energy technologies can help mitigate the environmental impact of trade openness and economic growth. Strengthening environmental regulations and promoting technology transfer will be crucial for achieving sustainable development across Central Asia.

The findings highlight important trade-offs between economic growth and environmental sustainability in Central Asian economies. While economic growth contributes to reducing emissions in the long run, energy consumption, trade openness, and foreign direct investment increase environmental pressure. This suggests that pursuing rapid growth without environmental safeguards may lead to higher emissions in the short to medium term. To balance these objectives, policymakers should adopt measurable targets such as reducing carbon intensity (CO₂ emissions per unit of GDP) by a specific percentage, increasing the share of renewable energy in total energy consumption, and improving energy efficiency in key sectors. In addition, setting clear environmental standards for foreign investment and introducing green trade incentives can help align economic expansion with sustainability goals. These policy targets can support a transition toward low-carbon growth while maintaining economic development momentum.

The empirical results also confirm that foreign direct investment and trade openness are factors that increase carbon emissions in the long run. Policymakers should adopt more stringent environmental protection policies for foreign investment projects and offer incentives for environmentally responsible and technology-driven investments. The promotion of green foreign direct investment, innovation, and clean production practices can mitigate the negative effects of economic globalization on the environment. Furthermore, trade policies should encourage the export of environmentally sustainable products and facilitate the transfer of clean technology. Finally, the negative long-term relationship between economic growth and carbon emissions indicates that sustainable economic development can lead to environmental improvement. Policymakers should incorporate environmental factors into their country's development plans and enhance regional cooperation on energy and environmental issues. A unified policy approach that focuses on renewable energy, green infrastructure, and sustainable industrialization can enable Central Asian na-

tions to achieve economic growth in the long term while mitigating environmental degradation.

Conclusion

This paper investigates the relationship between carbon emissions, economic growth, energy use, foreign direct investment, and trade openness in Kazakhstan, the Kyrgyz Republic, and Uzbekistan from 1997 to 2024. The Pooled Mean Group estimator in the panel Autoregressive Distributed Lag model was used to analyse the relationship between carbon emissions and their economic determinants. The results show that there is a long-run relationship between carbon emissions and their economic determinants. The results also show that energy use, foreign direct investment, and trade openness are factors that increase carbon emissions in the long run, but economic growth reduces carbon emissions. Energy use is the dominant factor that affects environmental degradation in the short run. Moreover, the results of the panel Granger causality test indicate that economic growth, foreign direct investment, trade openness, and energy consumption are all significant predictors of carbon dioxide emissions for the chosen Central Asian economies.

The study has made several contributions to the existing body of knowledge. Firstly, it has offered new empirical evidence on the energy–growth–environment nexus in Central Asia, a region that has been relatively underrepresented in the existing literature. Secondly, it has considered foreign direct investment and trade openness, providing a more complete picture of the factors that influence carbon emissions in transition economies. Thirdly, it has used a panel Autoregressive Distributed Lag model with the Pooled Mean Group estimator to capture both short-term and long-term relationships between countries with similar structural characteristics. The results of the study have helped to provide a better understanding of the role of economic development, globalization, and energy use in shaping environmental sustainability in resource-dependent economies.

Despite the contributions, the study has a number of limitations. Firstly, it has considered only three Central Asian economies because of data availability constraints, which may affect the generalizability of the results to other regions. Secondly, it has used aggregate measures of energy consumption and foreign direct investment without making a distinction between renewable and non-renewable energy sources and between different types of investment. Future studies may consider expanding the

sample to include other countries and use other variables such as the consumption of renewable energy resources, innovation, and environmental policy indicators to give a more nuanced analysis of environmental sustainability. Future studies may also use other econometric models to capture the complex relationships between economic activities and environmental outcomes.

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The Impacts of the COVID-19 Pandemic on National Economic Welfare: The Genuine Progress Indicator for Iceland

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This study assesses the economic impacts of the COVID-19 pandemic in Iceland using the Genuine Progress Indicator (GPI), an alternative macroeconomic measure that incorporates environmental and social externalities omitted from GDP. It updates Iceland's GPI from 2000–2023, with primary focus on the pandemic period (2019–2023), based on a methodology comprising 28 sub-indicators. Key findings reveal contrasting trends. While GDP fell by 6.0% in the pandemic's first year, the GPI showed sustained welfare levels. Government investments in education, health-care, and infrastructure more than offset rising social costs (mainly from unemployment) and declining environmental costs (notably reduced non-renewable resource use and greenhouse gas emissions). Following the full lifting of travel restrictions in 2022 and the tourism boom, both indicators rebounded strongly in 2022 and 2023. The GPI grew by 12.7% and 6.8%, while GDP increased by 18.7% and 11.0%. The results provide indications of Iceland's economic resilience during crisis and recovery.

Keywords: economic welfare, alternative measure, genuine progress, Iceland, pandemic

JEL classification: A10, I38

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Introduction

The COVID-19 pandemic unleashed multiple negative economic consequences, affecting economies of all scales and types (Delardas et al. 2022; Hong et al. 2023; Martin et al. 2020; Segal and Gerstel 2020). Median global Gross Domestic Product (GDP) reduced by 3.9% from 2019 to

2020, the greatest year-on-year decline since the Great Depression (International Monetary Fund 2021). The World Economic Forum (2020) described interconnected economic risks at the micro and macro levels, which included increased bankruptcies, prolonged recessions, high levels of unemployment, diminished fiscal positions, and disruptions to global supply chains. Reported systemic effects of the pandemic included, but were not limited to, destabilised tourism and hospitality sectors (Joo and Mir 2024), reduced food security (Nechifor et al. 2021), increased poverty (Decerf et al. 2021), increased inequality (Mahler et al. 2022), and diminished animal welfare and livestock supply chain sustainability (Hashem et al. 2020). Such risks were prevalent in developing nations and considered to be very common in remote and nature-dependent states, such as those in the Arctic (e.g. Greenland), which typically rely greatly on global connectivity for trade and tourism (Cook and Jóhannsdóttir 2021; Larsen and Petrov 2026; Peterson et al. 2023).

The shortcomings of using standard macroeconomic statistics, such as GDP, to measure economic welfare and societal progress have been well-described in the academic literature for many years (Coscieme et al. 2020; Costanza, Fioramonti et al. 2016; Costanza, Daly et al. 2016; Coyle 2015; Hoekstra 2019; Kubiszewski et al. 2013). The various limitations of the metric are valid regardless of the connotations of a pandemic. However, its deficiencies merely become starker amidst a seismic shock with global manifestations, many of which constitute non-market effects. In recent years there has been acknowledgement of the need to ‘move beyond GDP’ and utilise alternative or complementary tools to capture the broader implications of economic activity, including the positive contributions of voluntary work and leisure time, and the negative effects of income inequality, pollution, non-renewable resource depletion and crime, among other factors (Stiglitz et al. 2018; Hoekstra 2019; van den Bergh 2022). Coscieme et al. (2020, 6) called for ‘further macro-economic indicators that internalize social and environmental externalities’. This imperative has also been partially acknowledged within the United Nations’ Sustainable Development Goals (SDGs), wherein Target 19 of SDG 17 (Partnerships for the goals) demands the use of measurements of progress on sustainable development that complement GDP (United Nations 2015).

The Genuine Progress Indicator (GPI) is a popular ‘beyond GDP’ measure of economic welfare that has been calculated at the national, state and city level over the past three decades (Bagstad et al. 2014; La-

zarus and Brown 2022; Malinauskaite et al. 2026). It strives to provide 'a monetary measure of economic welfare for a given population in a given year that accounts for benefits and costs experienced by that population in association with investment, production, trade, and consumption of goods and services' (Talberth and Weisdorf 2017, 142). As far as the authors are aware, to date only one prior national GPI study in the published academic literature has sought to evaluate the impacts of the COVID-19 pandemic on the GPI and compared those outcomes to GDP, which was the Australian calculation by Karatopouzis et al. (2022), focused on the first six months of 2020.

The case study of the Icelandic GPI is used for the purposes of the analysis presented in this study, as this island nation provides a representative example of several of the international economic challenges caused by the COVID-19 pandemic – a sudden contraction in GDP, significantly increased unemployment, especially in tourism and related service industries, and disruptions to supply chains (Cook and Jóhannsdóttir 2021; Joo and Mir 2024; Marino and Pariso 2021; World Economic Forum 2020). In addition, the sensitive and turbulent recent history of the small and geographically isolated Icelandic economy (Duhs 2021; Halldórsdóttir et al. 2024) makes it well-suited for studying the impacts of macroeconomic shocks playing out on a global scale. A banking and currency value collapse in 2008 precipitated a tourism boom which, at one point, led to the nation having an annual GDP growth rate of 7.2%, the highest among all OECD members in 2016 (OECD 2017; Loftsdóttir 2018). More recently, restrictions on international movement caused by the COVID-19 pandemic led to the collapse of Iceland's tourism sector (OECD 2021; Sigurðardóttir 2020), which, after restrictions on international entrants were fully lifted, rallied strongly again during Q3 of 2022 (Iceland Chamber of Commerce 2022), reaching a record high in terms of international tourism consumption in 2023 (Statistics Iceland 2023).

This study seeks to evaluate the following research questions:

1. How do Iceland's GDP and GPI outcomes compare during the entire assessment period of 2000–2023?
2. What are the macroeconomic implications of the COVID-19 pandemic on national economic welfare during the specific period 2019 to 2023?
3. Which government interventions helped to mitigate the negative economic welfare consequences of the COVID-19 pandemic?

4. To what extent was Iceland's economic performance and management during the period 2019 to 2023 demonstrative of 'degrowth'?

Regarding the first research question, the decision to also evaluate across the longer time span of 2000–2023 in this study was motivated by two considerations. Firstly, this period also captures some of the turbulence of the Icelandic economy, such as the financial collapse of 2008, enabling an examination of how this shock played out with respect to both GDP and the GPI, and how it compared to the impacts of the COVID-19 crisis. Secondly, the longer time span enables us to observe the expansion in the Icelandic economy in the years up to 2019, the last year before the COVID-19 pandemic started, providing a standard for appraising the swiftness of the rebound in 2022 and 2023. In so doing, the study appraises both economic welfare (current levels of prosperity) through the GPI as well as the capacity for economic resilience, which includes the ability to withstand shocks and rebound. The focus of the explorative fourth research question on economic degrowth is motivated partly by calls in the international literature for the degrowth of carbon intensive sectors, such as tourism, in the aftermath of the COVID-19 pandemic, following observations of the decline in this sector's emissions during its incidence (Fletcher et al. 2020; Butcher 2023).

This article is organised as follows. The second section provides a brief overview of the impacts of the COVID-19 pandemic in Iceland. In the third section, the GPI method is presented. The fourth section outlines the results, which includes aggregate, per capita, and component analysis, and comparisons between the COVID-19 pandemic and the impacts of other macroeconomic shocks in the study period. The fifth section discusses the main outcomes and government efforts to mitigate costs during the pandemic, as well as providing broader methodological reflections. In the sixth section, the conclusion states key outcomes and some areas for further research.

Overview of the Impacts of COVID-19 in Iceland

HISTORY OF THE COVID-19 PANDEMIC IN ICELAND

The first COVID-19 infection was diagnosed in Iceland on 28th February 2020. By 27th September 2022, the total number of cases was 205,454, of whom 213 had died (Worldometer n.d.). Proportionally, 54.6% of all inhabitants had been infected at least once by the virus (Cook and Jóhannsdóttir 2021). Iceland's aggregate case numbers were very low in

a global context; however, the infection rate per 100,000 inhabitants was at times among the highest in the world, with large spikes in infections occurring in March 2020, September and October 2020, December 2021 and January 2022. Cook and Jóhannsdóttir (2021) described the use of a mixture of soft and hard measures to contain the pandemic in Iceland, which varied according to the extent of specific outbreaks. These included limitations on the types and size of gatherings (as low as groups of 10 people), with the intermittent closure of public venues such as swimming pools, cinemas, schools, businesses in the tourism sector and entertainment venues. In addition, there was frequently a widespread mandatory requirement for physical distancing, the wearing of masks and use of hand sanitiser in buildings accessed by the public.

The Icelandic Government initiated home-based quarantine, with very high levels of polymerase chain reaction (PCR) testing. In the period between 20th March 2020 and 1st July 2020, all foreign nationals, except those from the EU, EEA, EFTA, and UK, were not allowed to enter Iceland, although there were some special exemptions, and generally a 14-day period of quarantine was required for all. This approach started to evolve in December 2020 when Iceland began to accept certificates of previous infection at the border, positive PCR tests and international vaccination certificates. Thereafter, up until 25th February 2022, when all domestic and border restrictions were lifted, there was strict double testing at the border of returning visitors, initially with the inclusion of a minimum five-day period of quarantine in between tests, which was then adapted to a one-day quarantine if visitors had an approved certificate of vaccination (Cook and Jóhannsdóttir 2021). The adopted measures, in tandem with a rapid vaccination programme (90% of the population were vaccinated by November 2021), were mostly successful, with Iceland often the only European nation with a 'green' status in the weekly infection reports of the European Centre for Disease Prevention (2022).

ECONOMIC CONSEQUENCES AND GOVERNMENT RESPONSE IN ICELAND

The economic impacts of the pandemic on Iceland were considerable, especially in the six to nine months prior to the initiation of a vaccination programme. In the first nine months of 2020, the Government of Iceland (2020) estimated that gross factor income linked to tourism, the nation's most significant export industry, was reduced by around 60% compared to the same period in 2019. Unemployment levels in Iceland

reached their highest levels since 2012, with a national average of 12% reported in June 2020. However, there was considerable regional variability. In Suðurnes, an unemployment rate as high as 26% was reported in January 2021 (Statistics Iceland 2021). Much of the unemployment across Iceland related to lost jobs in the tourism industry and related hospitalities (Cook and Jóhannsdóttir 2021).

The combination of border and domestic restrictions led to a reduction in international visitors from just over 2 million in 2019 to just under 500,000 in 2020, a precipitous 76% fall. This increased by 44% to nearly 700,000 in 2021, which was still 65% below the 2019 total, but after all restrictions on international entrants were lifted early in 2022, visitor numbers increased to 1.7 and 2.2 million in 2022 and 2023, respectively (Icelandic Tourist Board n.d.). The cruise ship industry also suffered in the first year of the pandemic, with the number of visitors reducing from 549,000 in 2019 to 2,300 in 2020, a 99.6% decline (Icelandic Tourist Board n.d.). Other major economic effects in Iceland included supply chain disruptions, especially in fisheries. This led to significant reductions in the profits of some companies – for example, Iceland Seafood International reported sales in the first six months of 2020 of 183.2 million Euros, a reduction of 21% compared to the corresponding period in 2019 (Holland 2020).

The Icelandic Government rapidly put forth various economic packages to support the fiscal balance and general economic and societal stability and resilience during the COVID-19 pandemic. These related predominantly to benefits and wage financing; subsidies, grants and funds; and targeted marketing and support measures for the recovery (Cook and Jóhannsdóttir 2021). Regarding benefits and wage financing, these included temporary increases in unemployment benefits, partial compensation schemes for partial unemployment, child benefit supplements, payment of wage costs during notice periods, payment of wages during quarantine, and repayment of Value Added Tax for home improvement works and domestic construction activities. In terms of subsidies, grants, and funds, the main elements encompassed income loss subsidies for the self-employed, resilience subsidies for companies suffering at least 40% reductions in revenues, closure subsidies, and hiring grants. Targeted marketing and support measures included front-loading of investment, international marketing campaigns to promote future tourism, and Travel Gift vouchers to promote domestic tourism during the pandemic (Cook and Jóhannsdóttir 2021).

Methodology

THEORETICAL UNDERPINNINGS OF THE GPI

Over the years, there have been various perspectives set out on the theoretical underpinnings of the GPI, which have contributed to sometimes diverse methodological approaches and selection of sub-indicators. We do not seek to offer a comprehensive review of them all, which has been provided in recent publications such as Malinauskaite et al. (2026), but rather to emphasise that in seeking greater methodological standardisation, Talberth and Weisdorf (2017) affirmed four distinguishing methodological principles that should be adopted in any GPI study: (1) emphasis on final consumption of market and non-market goods and services by a given population in a specific period of time; (2) focus on quantifying current economic welfare generated by consumption; (3) inclusion of only costs and benefits that are demonstrably linked to economic activities; and (4) monetisation of costs and benefits to be applied using best available data and peer reviewed methods. These reasonings provide the basis for the GPI method adopted in this study.

CALCULATION OF THE ICELANDIC GPI

The pilot Icelandic GPI study by Cook and Davíðsdóttir (2021) adhered to the GPI 2.0 method piloted by Talberth and Weisdorf (2017) in terms of its functional form, as represented by equation (1), and the same framework is applied in this version. For a specific period (each year) and population (Iceland's), equation (1) aggregates utility from the consumption of goods and services to utility sourced from various capital assets, then deducts disutility from undesirable environmental and social conditions.

Equation (1):

$$GPI_t = \frac{1}{N} \left[U_i((HBE_i - DEFR - HI_i) \times INQ + PP)_i \right. \\ \left. + U_i(s(KH_i + KS_i + KB_i)) \right. \\ \left. - dU_i(DKN_i + POL_i + SC_i) \right], \quad (1)$$

where:

- U is utility
- DU is disutility
- HBE are household budget expenditures
- $DEFR$ are defensive and regrettable expenditures

- HI are household investments
- INQ is an income inequality adjustment
- PP are public provision of goods and services
- s is services
- KH are services from human capital
- KS are services from social capital
- KB are services from built capital
- DKN is depletion of natural capital
- POL is pollution
- SC are social costs of economic activity

Based on the lessons learned from the Icelandic GPI pilot study of Cook and Davíðsdóttir (2021) and the critique of the GPI 2.0 method provided by Malinauskaite et al.'s (2026) systematic literature review, this study's method omitted variables of negligible scale, including costs of overharvesting fisheries, avoided environmental depletion costs by government, and government expenditures on recreation, culture, and religion; those potentially likely to lead to double counting, such as ozone depletion costs duplicating the climate change contribution costs; or those associated with considerable uncertainty. Regarding the latter, the estimated aggregate value for Iceland's ecosystem services, which constituted 108% of the value of Iceland's GDP in 2019 (Cook and Davíðsdóttir 2021), has been left out of this study. This was because it was based on a single, somewhat crude order of magnitude approximation by benefit transfer (Cook and Davíðsdóttir 2022), had a distortionary impact on the overall results, and because scarcely any primary non-market valuation studies are available in an Icelandic context from which to form a reliable alternative estimate.

Table A1 in the Appendix provides a detailed summary of the GPI methodology adopted in this study, outlining the calculation methods which were used for each sub-indicator and related data sources. A total of 28 sub-indicators were included, specific to the three main categories and sub-categories of economic welfare expressed by equation (1). All costs and benefit components were adjusted for inflation and reflected constant 2023 prices in the currency of Icelandic króna. Some values for the 2023 year were not yet available, such as for the Gini coefficient. As these calculation inputs had demonstrated very little variability in recent years, they were assumed to be unchanged from their 2022 values.

Results

OVERALL TRENDS FROM 2000 TO 2023

Figures 1 and 2 provide a comparison of Iceland's GDP and GPI over the period 2000 to 2023 with respect to aggregate and per capita values. All values are stated in constant Icelandic prices (2023) in either trillion or million ISK (T or M ISK), with commensurate values in million euros provided in brackets afterwards. These were based on the average exchange rate throughout 2023 of 1 ISK to 0.006706 Euros.

During the years 2004 to 2007 and 2012 to 2020, Iceland's GPI exceeded GDP (albeit narrowly in 2015), lagging behind only during the period 2000 to 2003 and in the aftermath of the banking-induced crisis of 2008. Unlike the five years required for Iceland's GPI, its GDP aggregation only took eight years to recover to its former zenith of 2008. In the period of the COVID-19 pandemic, only Iceland's GDP contracted, and the degree of divergence between GDP and the GPI remained consistent, with the same trend evident in the per capita data.

Starting at 2.04 T ISK (13,685 M€) in 2000, GDP grew steadily. Early growth was robust, peaking at 3.16 T ISK (21,187 M€) in 2008 (a 54.8% increase from 2000), driven by a booming financial sector and increased construction activity (Duhs 2021; OECD 2021). However, the 2008 financial crisis triggered a sharp decline, with GDP falling to 2.87 T ISK (19,251 M€) in 2009 – a 9.1% drop – reflecting Iceland's banking collapse and

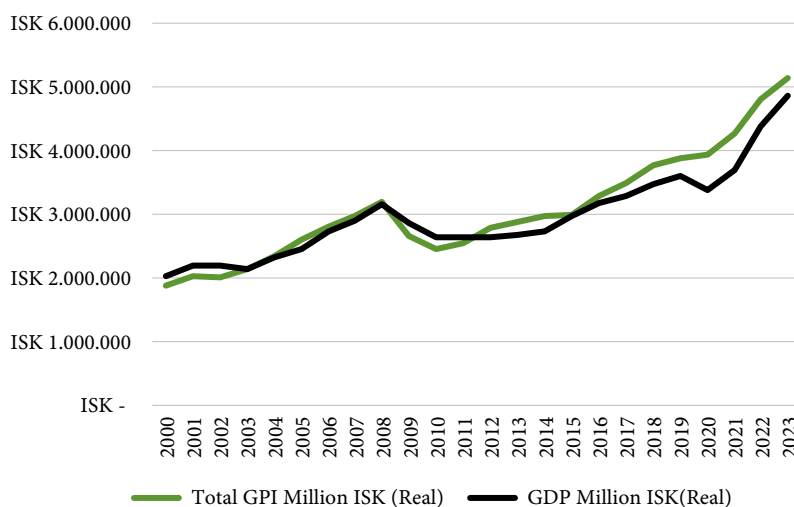


FIGURE 1 Icelandic GDP Versus GPI, 2000–2023 (M ISK, 2023 prices)

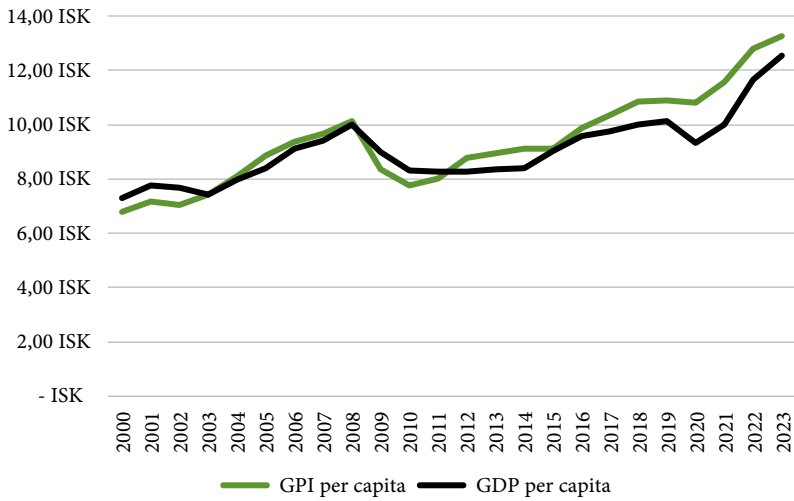


FIGURE 2 Icelandic GDP Versus GPI, 2000–2023 (M ISK per capita, 2023 prices)

currency depreciation (Bryant and Sigurjónsson 2022). Post-crisis recovery began in 2010, with GDP stabilising at 2.64 T ISK (17,734 M€) and then accelerating, particularly after 2015, fuelled by increased tourism and export growth (Duhs 2021). By 2023, GDP reached 4.86 T ISK (32,610 M€), a 138% increase from 2000 and a compound annual growth rate (CAGR) of 3.8% over the full period. Despite the blip in 2020 linked to the COVID-19 pandemic, the most significant growth occurred post-2015, with an average annual increase of 6.6% from 2015 (2.97 T ISK; 19,949 M€) to 2023, much of which was linked to Iceland’s post-2012 tourism expansion (Bryant and Sigurjónsson 2022).

The GPI also rose over the entire assessment period but with distinct differences in pace and volatility. Starting at 1.89 T ISK (12,659 M€) in 2000, the GPI grew to 3.2 T ISK (21,410 M€) by 2007, surpassing GDP’s growth rate in this phase. In contrast to GDP, the GPI’s post financial crisis dip was more severe, falling to 2.67 T ISK (17,884 M€) in 2009 (a 16.5% decline). From 2010, the GPI recovered steadily, hitting 3.89 T ISK (26,053 M€) in 2019, a 105.8% increase from 2000, before increasing only slightly (1.2%) to 3.93 T ISK (26,368 M€) in 2020 due to the pandemic’s impact on tourism and social costs. By 2023, the GPI reached 5.14 T ISK (34,494 M€), a 172.5% rise from 2000 and a CAGR of 4.4%.

While both the GDP and GPI trend is upward, GPI consistently exceeded GDP in real terms from 2015 onward, reflecting its inclusion of positive non-market contributions (e.g. services from social and built capital) and

adjustments for negative externalities (e.g. pollution and greenhouse gas emissions). In 2000, the GPI was 92.5% of GDP, but by 2023, it was 105.8%, peaking at 114.8% in 2020. This divergence highlights that Iceland's economic growth increasingly translated into broader societal benefits in the period after the 2008 financial crisis, though not uniformly. Key inflection points reveal distinct patterns. Pre-2008, GDP outpaced the GPI (e.g. 2006: GDP of 2.73 T ISK vs. GPI of 2.82 T ISK; 18,320 vs. 18,878 M€), reflecting growth driven in part by financial speculation (Bryant and Sigurjónsson 2022), with rising environmental (e.g. greenhouse gas emissions) and social costs (e.g. costs of commuting). Post-2008, the GPI's recovery was stronger, driven by factors such as reduced inequality (the indexed Gini-based income distribution improved from 120.26 in 2008 to 107.0 in 2023) and increased leisure time (adjusted mean individual leisure time rose from 1,699 hours in 2008 to 1,789 hours in 2023).

Demonstrating similar patterns to the aggregate data, GDP per capita grew from 7.31 M ISK (0.05 M€) in 2000 to 12.54 M ISK (0.08 M€) in 2023 (a 71.6% increase), while GPI per capita rose from 6.76 (0.05 M€) to 13.27 M ISK (0.09 M€), a 96.2% increase. This gap again underscores the GPI's emphasis on broader welfare gains outstripping raw macroeconomic output per person, particularly as the Icelandic population grew in this period from 279,049 to 387,758.

GDP AND THE GPI DURING THE COVID-19 YEARS: 2019 TO 2023

In 2019, Iceland's GDP stood at 3.61 T ISK (24,206 M€), reflecting a strong pre-pandemic economy driven by tourism and fisheries (Duhs 2021). The onset of COVID-19 in 2020 led to a sharp decline, with GDP dropping to 3.39 T ISK (22,749 M€) – a 6.0% reduction. This contraction was largely due to the collapse of tourism, a key economic driver, as international travel restrictions prevented visitors (Central Bank of Iceland 2021). Household consumption also stabilised (1.81 T ISK in 2019 vs. 1.82 T ISK in 2020; 12,145 vs. 12,174 M€), unlike in the years 2021 to 2023, when growth was evident.

Macroeconomic recovery began in 2021, with GDP rising to 3.69 T ISK (24,750 M€), an 8.8% increase from 2020), fuelled by domestic stimulus, a partial tourism rebound, and strong exports (especially of fresh and frozen fish), which were 21.8% higher in economic value than in 2020 (Statistics Iceland 2022). By 2022, as travel restrictions eased and global demand strengthened, Icelandic GDP increased to 4.38 T ISK (29,373 M€),

a growth of 18.7% from 2021. As tourist numbers in Iceland rebounded to pre-pandemic highs, this momentum continued into 2023, with GDP growing by 11.0% to reach 4.86 T ISK (32,611 M€). This constituted a 34.7% increase from 2019 and a CAGR of 7.7%. Per capita GDP rose from 10.11 M ISK (0.07 M€) in 2019 to 12.54 M ISK (0.08 M ISK) in 2023 (24.0% growth), despite population growth from 356,991 to 387,758 inhabitants.

The GPI started at 3.88 T ISK (26,040 M€) in 2019, rising slightly to 3.93 T ISK (26,368 M€), a 1.3% increase, in 2021, in stark contrast to GDP's decline. This resilience stemmed from gains in non-market factors: services from social capital increased (1.88 to 1.91 T ISK; 12,583 to 12,783 M€), leisure time grew (adjusted mean individual leisure time rose from 1,735 to 1,789 hours as work hours dropped from 39.6 to 38 per week), and environmental costs fell. However, social costs spiked, especially unemployment (0.08 T ISK in 2019 vs. 0.14 T ISK in 2020; 545 vs. 911 M€), constraining gains.

In 2021, the GPI increased to 4.27 T ISK (28,656 M€) (8.7% growth), aligning with GDP's recovery, which was driven in part by the reduction in the Central Bank's main interest rate to a record low of 0.75% at the end of 2020 (Central Bank of Iceland 2020), and expanded public services (e.g. healthcare expenditure increased from 0.31 to 0.34 T ISK; 2,075 to 2,249 M€). By 2022, GPI reached 4.81 T ISK (32,288 M€), 12.7% growth on 2021, surpassing GDP growth as leisure time benefits persisted and environmental costs remained stable. In 2023, the GPI reached 5.14 T ISK (34,494 M€), which was 6.8% growth on 2022, a 32.5% increase from 2019, and a CAGR of 7.3% over the period 2019–2023. GPI per capita grew from 10.88 M ISK (0.07 M€) in 2019 to 13.27 M ISK (0.09 M€) in 2023 (22.0% expansion), slightly lagging GDP per capita growth.

The pandemic exposed a brief divergence between GDP and the GPI. In 2020, GDP fell by 6.0% while the GPI rose by 1.3%, reflecting its sensitivity to predominantly economic (e.g. increased public expenditures on healthcare and education), but also non-economic, gains (e.g. reduced environmental damages, such as non-renewable resource depletion, and increased leisure time, despite economic contraction). The GPI's 2020 peak relative to GDP (115.9% of GDP vs. 107.6% in 2019) underscores this disconnection. Post-2020, both metrics recovered strongly, but the GPI's growth was steadier (an average annual increase of 9.2% from 2020–2023 vs. GDP's 12.8%), driven by sustained social and environmental adjustments. Key drivers of the GPI's resilience included a pronounced drop in costs relating to natural capital depletion (e.g. oil

use fell from 43.3 PJ in 2019 to 24.6 PJ in 2020, albeit it has rebounded from 2022 onwards) and reduced overemployment costs (from 0.08 T ISK [545 M€] in 2019 to zero in 2020 as average work hours fell). Meanwhile, GDP's swift recovery reflected the tourism sector's swift rebound (e.g. household consumption rose from 1.82 T ISK (12,174 M€) in 2020 to 2.56 T ISK (17,157 M€) in 2023) and export income strength (e.g. the economic value of exports was 31.4% higher in 2022 than 2021 (Statistics Iceland 2023)).

GPI CATEGORY ANALYSIS FROM 2019–2023

Table 1 displays an analysis of changes in the three main aggregate category values of the Icelandic GPI from 2019 to 2023, with a more detailed sub-component breakdown provided in Table A.2 in the Appendix.

As evidenced in table 1, utility from goods and services was 2.43 T ISK in 2019, driven by robust consumption and public spending. In 2020, utility from goods and services fell slightly by 0.2% to 2.42 T ISK (16,241 M€), but otherwise it grew each year. Consumption held fairly steady initially (a 2.19% drop in 2020), but public healthcare spending grew from 0.31 to 0.34 T ISK (2,075 to 2,249 M€) from 2020 to 2021 and expenditure on education increased by 14.3% between 2019 and 2020, helping to more than offset increased defensive and regrettable expenditures in 2020. As the pandemic's social and economic restrictions started to wane, unadjusted consumption in 2023 was 41.0% higher in 2023 than in 2019, with only a negligible change to income inequality. Overall, the 33.6% rise in

TABLE 1 GPI Category Analysis, 2019–2023 (values in 2023 prices)

Category		2019	2020	2021	2022	2023
Utility from consumption of goods and services	M ISK	2,426,725	2,421,840	2,664,229	3,016,713	3,241,815
	% change yearly		(0.20)	10.01	13.23	7.46
Utility from capital assets	M ISK	1,954,506	1,996,805	2,098,363	2,252,578	2,357,289
	% change yearly		2.16	5.09	7.35	4.65
Disutility from undesirable environmental and social conditions	M ISK	(498,134)	(486,661)	(489,431)	(454,475)	(455,316)
	% change yearly		2.30	(0.57)	7.14	(0.19)
Total	M ISK	3,883,097	3,931,984	4,273,161	4,814,816	5,143,788
	% change yearly		1.26	8.68	12.68	6.83
Euro equivalent (millions)		26,040	26,368	28,656	32,288	34,494

utility from goods and services over 2019–2023 mirrors GDP's recovery (34.7%), highlighting its role as both a core GDP and GPI element.

Services from capital assets (human, social, and built capital) capture non-market contributions to well-being. In 2019, these totalled 1.95 T ISK (13,107 M€), with social capital (1.87 T ISK; 12,543 M€) dominant, reflecting the estimated economic benefits of volunteer work and leisure time. In 2020, this rose by 2.2% to 2.00 T ISK (13,391 M€), as social capital increased to 1.91 T ISK (12,783 M€) due to leisure gains (1,789 hours) from reduced work hours (39.6 to 38 weekly). Built capital (13,018 M ISK; 87 M€) and human capital contributions, although insignificant contributors to the category total, also grew modestly. In 2021, this component jumped 5.2% to 2.10 T ISK (14,072 M€), with social capital at 2.00 T ISK (13,407 M€). In 2022, this reached 2.25 T ISK (15,106 M€) (7.4% growth), and by 2023, it hit 2.36 T ISK (15,808 M€) (4.6% growth), a 20.6% increase compared to 2019. Social capital (2.26 T ISK; 15,129 M€) remained the backbone, bolstered by increased leisure time benefits of 20.8% from 2019 to 2023.

Aggregate environmental and social cost deductions for natural capital depletion, pollution, unemployment, crime, commuting, and accidents fell from 0.50 T ISK (3,340 M€) in 2019 to 0.46 T ISK (3,053 M€) in 2023, an 8.6% decrease. At the outset of the pandemic in 2020, combined environmental and social costs dropped 2.3% overall to 0.47 T ISK (3,264 M€), as environmental costs fell, with fossil fuel consumption falling from 43.3 to 24.6 PJ. However, within this combined category, unemployment costs still soared (0.14 T ISK vs. 0.81 T ISK; 911 vs. 545 M€) due to pandemic layoffs. In 2021, environmental and social costs rebounded by 0.6% to 0.49 T ISK (3,282 M€). By 2022, environmental and social costs fell again to 0.45 T ISK (3,048 M€), largely due to a 34.4% drop in the numbers listed as unemployed.

Discussion

CONTEXTUALISATION OF OUTCOMES AND GOVERNMENT EFFORTS TO MITIGATE ECONOMIC DAMAGES

As far as the authors are aware, the only national GPI study broadly comparable to this one is the examination of the Australian GPI in the first six months of 2020 by Karatopouzis et al. (2022). However, those outcomes cannot be directly compared since this study accords with the more comprehensive, capital asset-based GPI 2.0 method advocated by Talberth and Weisdorf (2017) and Cook and Davíðsdóttir (2021). Karatopouzis et al. (2022) also utilised fewer sub-indicators – 20 as opposed

to the 28 selected in this study. However, despite the focus on only two economic quarters rather than the entirety of the COVID-19 pandemic and the variables omitted by Karatopouzis et al. (2022), such as the economic value of economic services and public provision of goods and services, which have considerable aggregate value in the Icelandic GPI, some commonalities can be observed in the outcomes of the respective studies specific to the sub-indicators that are aligned and which rely on similar calculation methods. The study outcomes affirm similar overall findings, namely that the pandemic restricted the capacity of individuals to earn and consume, and that related social and economic costs exceeded any environmental benefits.

The health policy responses of the Icelandic government, prioritised the need to protect public health, and therefore restrictions on gathering limits and opening hours occurred with a swiftness that had negative economic connotations for employment and consumption, albeit, in the case of the latter, not to the same degree as had been evident during Iceland's financial crash of 2008. The Icelandic financial collapse of 2008 was associated with widespread business bankruptcies and unemployment was particularly linked to finance and related sectors, and there was a sudden halt in foreign investment and credit. In contrast, the COVID-19 pandemic, starting in 2020, hit Iceland's economy through a different mechanism: a collapse in tourism, which had become the country's largest export sector by then, accounting for over 40% of exports pre-pandemic (Duhs 2021; OECD 2021). The Icelandic government were able to mitigate this to some extent through both fiscal and monetary policy measures, including payments of a significant share of wages (Grout et al. 2023), incentives to encourage domestic tourism, and a reduction in the Central Bank's main interest rate to a record low of 0.75% in November 2020 (Central Bank of Iceland 2020). These approaches helped to sustain domestic consumption, which increased in real terms by 0.2% in 2020 compared to 2019.

The 0.2% growth in consumption in Iceland between 2019 and 2020 was markedly different to the outcome in the Australian GPI. This was particularly evident in Q2 of 2020 when the effects of the pandemic were felt more strongly than in Q1. Consumption declined by 34 billion AUS \$, equal to 12.8%. Similarly to the Icelandic case, increased costs of unemployment in the Australian GPI of 23.4% more than offset the fall in environmental costs (Karatopouzis et al. 2022). In 2020, environmental costs declined by 5.5% in the case of Iceland and 3.1% in Q2 of the Australian

GPI. The greater percentage reduction in Iceland was driven by a 4.3% reduction in the costs of climate change and the 76.0% diminishment in non-renewable resource consumption in 2020 compared to 2019. For other comparable sub-indicators, the Australian GPI also provided evidence of reduced costs of crime and family changes. Although likely driven by different methodological approaches by Karatopouzis et al. (2022), such as adopting a net revenue rather than social payoff approach for valuing the benefits of higher education, the value of higher education reduced by 12.8% in Q2 of the Australian GPI, unlike in Iceland's case, where it increased by 3.3%.

The OECD (2022) had reported in June 2022 that a resurgent tourism sector, reduced unemployment and increased flows of foreign currency were likely to lead to growth in Icelandic GDP of 4.2% in 2022 and 2.8% in 2023. In the end, GDP growth of 18.7% and 11.0% was delivered in 2022 and 2023, respectively. Many of the support payments made by the Icelandic government in 2020 and 2021, especially income loss and resilience subsidies, and targeted marketing campaigns, may have played a role in this recovery. Initially, there was a strong focus on promoting domestic tourism during the pandemic, as international arrivals in 2020 fell by 76% (Grout et al. 2023; Icelandic Tourist Board n.d.). This included advertising campaigns and small economic inducements, including a Travel Gift Voucher worth 5,000 ISK, which could be used as a form of payment in most Icelandic tourism companies, and was issued in both 2020 and 2021 (Grout et al. 2023). In tandem with the lowering of interest rates and various measures taken to provide financial support to business and the unemployed, such initiatives likely helped to ensure that Icelandic consumption did not fall during the pandemic, minimising the scale of the one-year recession in GDP, and ensuring that the GPI did not reduce at all from 2019 to 2023. Other efforts made by the Icelandic government to ensure economic stability and a swift post-pandemic rebound included allowing individuals to claim unemployment benefits at the same time as undertaking educational training. These were reflected as increased social costs in the GPI in 2020 and 2021, but they could partially be conceived of as investments. Furthermore, aided and abetted by the first volcanic eruption in the vicinity of Reykjavík for around 800 years in 2021 (Barsotti et al. 2023), a successful international marketing campaign, carried out as a collaboration between the Icelandic Government and the Icelandic Agency for Promotion and Marketing Offshore, helped to encourage foreign tourists to return to Iceland rapidly once the

pandemic's restrictions were fully lifted in 2022 (Grout et al. 2023). This proved to be effective, with tourist numbers in 2023 already exceeding the level observed in 2019, almost matching the 2018 peak and exceeding it in terms of nights stayed (Icelandic Tourist Board n.d.).

Other key economic endeavours by the Icelandic government included the increased investment in healthcare and infrastructure – in the case of the former, by allocating additional funds to public healthcare to deal with the emergency medical situation; for the latter, by front-loading public investment, especially related to transportation, tourism, and technology infrastructure. This leads to the observation that although the GPI, as conceived by Talberth and Weisdorf (2017) and reflected in their GPI 2.0 method, is intended to be a measure of current economic welfare, during a crisis event such as the COVID-19 pandemic, to some extent it also reflects economic resilience to shocks, since considerable shares of the government's public expenditure on healthcare and education were defensive endeavours undertaken to minimise damages, rather than realise any welfare benefits e.g. reducing pandemic death rates through purchases of personal protective equipment and diminishing rates of educational dropouts by paying unemployment benefits alongside university study (Hall et al. 2022; Hultkrantz and Svensson 2022).

The Icelandic approach to maintaining economic resilience, as reported by Cook and Jóhannsdóttir (2021), had some similarities to the island case of Greenland, whereby government expenditure on health was increased to minimise the potential for systemic risk events, and investment was viewed as the bedrock of economic resilience and recovery. The focus of both Iceland and Greenland on tourism was interesting in the light of the OECD's (2021) assertion that Iceland's economy had become too dependent on tourism and required further diversification. This may be correct, and the COVID-19 pandemic highlighted specific vulnerabilities and dependencies, but it perhaps does not recognise that tourism had already proven to be an effective means for Iceland of diversifying and recovering in the aftermath of a far deeper economic crisis – the banking and financial collapse of 2008 (Mixa and Loftsdóttir 2021). Moreover, further short-term diversification of island economies with small populations in often inhospitable climates, such as Greenland and the Faroes, is challenging, certainly in the short to medium term (Armstrong and Read 2021). Thus, in the case of Iceland, economic resilience and recovery was not about sectoral diversification, but rather the enhancement of existing strengths and 'being ready' in terms of infrastruc-

ture provision for the post-pandemic economic rebound, an approach that has also been evident in Southeast Asia (Deloitte and Infrastructure Asia 2020), Iran (Hajilo et al. 2024), and Botswana (Kenalemang and Stephens 2025).

BROADER REFLECTIONS ON DEGROWTH, THE THRESHOLD HYPOTHESIS, AND POLICY IMPLICATIONS

Given the contraction in Icelandic GDP and reduction in environmental costs in the GPI over the period 2019–2020, and perhaps by accident rather than government intention, the effects of the COVID-19 pandemic may have exemplified several of the features often advocated within the degrowth (Kallis 2011) or ‘agrowth’ movements (van den Bergh 2022), as well as the doughnut economy framework of Raworth (2017) whereby economic activities do not contribute to the exceedance of planetary boundaries and minimum social needs are fulfilled. For the purposes of this study, the GPI was a particularly useful metric for evaluating many of the broader macroeconomic and socio-economic implications of the COVID-19 pandemic, many aspects of which have parallels to policy interventions advocated in degrowth economics. These include approaches such as universal basic income, strict limits to greenhouse gas emissions, embracing flexible and part-time working, and creation of public money (Kallis 2011; Kallis et al. 2025; Karatopouzis et al. 2022). Constrained consumption, especially of non-renewable resources, was evident and induced by a combination of measures, especially gathering and travel restrictions and limits on the opening of economically important activities (Cook and Jóhannsdóttir 2021).

Although not universally applied and with some conditions, the range of Icelandic government support payments for the unemployed and business support packages were akin to a trial of universal basic income, especially when wages were paid by the state during notice periods and quarantine. Despite this, the use of the GPI should still be regarded with some caution for those envisioning transitions to post-growth futures. The devil is in the details of the GPI, rather than its headline outcomes. As was evident in Iceland’s GPI in 2023, growth in utility from consumption of goods and services can outpace slightly increased environmental and social costs, leading to an overall increase in the value of the GPI, all other factors being equal. Overemphasis on the GPI’s aggregate outcomes could, therefore, promote weak sustainability (Hoekstra 2019) and prolong a growth-focused narrative, potentially beyond the point at

which critical ecological thresholds will have been breached (Neumayer 2000). Furthermore, the GPI places a narrow lens on costs and benefits occurring in a particular place and at a specific point in time. It does not account for costs that are shifted abroad, such as carbon intensive production methods (Van der Slycken and Bleys 2020), or unaccounted for, such as greenhouse gas emissions linked to international aviation.

Several GPI policy implications were identified in the recent systematic literature review by Malinauskaite et al. (2026). These included raising awareness about the economic and social trade-offs of different macroeconomic policies and highlighting both the positive and negative welfare impacts of economic activity, including non-market components. For the most part during the assessment period, and entirely after the year 2017, the Icelandic GPI remained above GDP, with no convergence. This outcome sits in contrast to much of the GPI literature, which reports threshold effects due to economic and social trade-offs. First described by Max-Neef (1995) and supported by considerable empirical evidence (Kubiszewski et al. 2013; Long and Ji 2019; Van der Slycken and Bleys 2020), the threshold hypothesis contends that after a certain degree of GDP growth, economic activities become uneconomic, with the environmental and social costs of macroeconomic expansion exceeding the benefits. Others have suggested that Max-Neef's (1995) threshold hypothesis is caused by methodological flaws in the GPI rather than welfare effects (Dietz and Neumayer 2006). The efforts of Talberth and Weisdorf (2017) to try and establish greater standardisation in the GPI's methodology through the GPI 2.0 method, especially for the purposes of establishing greater theoretical rigour and to enable easier comparison between the outcomes of national studies, have had limited success to date (Malinauskaite et al. 2026). However, in the two national studies to date to adopt the GPI 2.0 method on the US and Iceland (Talberth and Weisdorf 2017; Cook and Davíðsdóttir 2021), which places greater focus than earlier methods on including the monetary value of multiple services from capital assets and current economic welfare (Malinauskaite et al. 2026), neither found any evidence in support of the threshold hypothesis. In both these national studies, as in this case, economic growth was not found to be 'uneconomic' in recent years.

This Icelandic case study also contributes to the wider international 'beyond GDP' policy debate by demonstrating how the GPI can provide a more multidimensional assessment of economic performance during periods of crisis than conventional GDP measures alone. In line with

growing international calls for complementary welfare indicators within sustainable development policy (Costanza et al. 2014; Van der Slycken and Bleys 2020; Malinauskaite et al. 2026), the Icelandic results illustrate how social protection measures, public healthcare investment, leisure time, and environmental externalities materially shaped national welfare outcomes during the COVID-19 pandemic, despite contractions in GDP. The findings therefore reinforce longstanding arguments within the broader post-growth and wellbeing economy literature that macroeconomic resilience cannot be adequately evaluated through production-based indicators alone. Even though the trade-off of increased social costs was perhaps inevitable given surging unemployment during the COVID-19 pandemic, this study's GPI results imply that macroeconomic welfare need not decline overall, especially if priority is given by policy-makers to targeted expenditures on education and healthcare and investing in domestic industries. As Martinez et al. (2021) contend, this approach, adopted by many national governments during the COVID-19 pandemic, could be conceived of as a classic Keynesian injection via increased government spending, as a means of resolving unemployment and boosting aggregate demand.

METHODOLOGICAL REFLECTIONS AND STUDY LIMITATIONS

Several methodological challenges and pitfalls in this study's GPI method were evident, some of which were of specific importance to assessing the macroeconomic impacts of a crisis event such as a pandemic through the GPI. The first, more general observation, concerns the typical emphasis in GPI studies of comparing growth rates with those of GDP. Given that the GPI 2.0 method includes several additional benefits that are commonly excluded from GPI 1.0 studies, and in some cases exceed the value of GDP, comparing the percentage growth rate of GPI with GDP always constitutes a somewhat misleading analysis given the different scales of the aggregations. Another issue concerns the availability of timely data. Hoekstra (2019), Cook and Davíðsdóttir (2021) and van den Bergh (2022), among others, have highlighted this as one of the main reasons why alternative measures of economic welfare have not become institutionalised, at least nowhere near to the same extent as the United Nation's System of National Accounts used for calculating GDP. In this study, some data omissions were evident in 2023, and these may have had an impact on the GPI outcome. In particular, the lack of a Gini coefficient calculation of income inequality in Iceland since 2022 may have

had an influence on outcomes when adjusting consumption, although the adjustment was less than 10% for eleven of the twelve previous years. Time lags and gaps in collating environmental data are common and longstanding, having been reported before in Iceland (Saviolidis et al. 2021).

A further limitation of the consolidated GPI 2.0 method adopted in this study concerns the focus on current economic welfare in a particular period, which, although called for by Talberth and Weisdorf (2017) study, can lead to mixed messages about the extent to which the GPI should capture information about the sustainability of economic activity. An increased debt burden likely imperils the level of future consumption and utility sourced from goods and services in the GPI. Such macroeconomic implications and dynamics have largely been ignored in the recent GPI literature, despite Kenny et al. (2019) calling for further such analysis. Other economic problems in Iceland, not captured by the GPI, have related to the historically low interest rates applied by the Central Bank of Iceland in 2020, which contributed to high price inflation in subsequent years (Harðarson 2024). A further limitation of a national GPI study such as this, especially when examining crisis consequences, concerns the lack of any exploration of regional and demographic variations in outcome. As reported by Statistics Iceland (2021), the unemployment rate in the Suðurnes region of Iceland in 2021 was more than double the Icelandic average, with young people working in the service industries hit especially hard, and these nuances are missed. Furthermore, there remains the potential for some double counting in the method, with the social cost of carbon incorporating the costs of deaths from air pollution. Moreover, although increased leisure time was always regarded as a benefit in the calculation, it very likely could have often been a cost, given the increased loneliness, isolation, and mental health challenges experienced by many during the COVID-19 pandemic (Cook and Jóhannsdóttir 2021). In addition, although omitted for reasons of considerable uncertainty and due to the aforementioned scale impacts on the GPI outcomes in the Icelandic pilot study by Cook and Davíðsdóttir (2021), inclusion of the economic value of Iceland's non-market ecosystem services, ideally including dynamic evaluation of changes over time throughout the pandemic, would have provided a more nuanced assessment. If the same estimated aggregate ecosystem services value had been used in this study, as per Cook and Davíðsdóttir (2021), then the Icelandic GPI would have always been two to three times greater than GDP across the assessment

period, but with the consequence that environmental and social costs were dwarfed in comparison.

This study thus also exemplifies several of the methodological criticisms of the GPI 2.0 method distinguished by Malinauskaite et al. (2026) in a recent systematic literature review with a global focus. This found that there seems to be little evidence of any methodological standardisation in recent GPI studies, which greatly constrains the potential for international comparisons. Moreover, many authors still use the earlier ‘GPI 1.0’ method and are ad hoc in terms of their sub-indicator selections, with these being determined by authors rather than any form of robust stakeholder-focused evaluations. Additionally, the adoption of sensitivity analysis on dominant cost and benefit components is very uncommon. A final factor of importance concerns the possible weightings of the included cost and benefit components in the GPI calculation, with these currently regarded as being of equal importance. Deliberations with stakeholders could also help to identify the degree of influence each has on welfare, ensuring the monetary values for the GPI’s sub-indicators are not all equally weighted.

Conclusion

Analysing the trends in GDP and GPI for Iceland from 2000 to 2023 provided insights into economic growth and broader economic well-being and resilience. The assessment period spanned a period marked by economic booms, a severe financial crisis, subsequent recovery, and the challenges of the COVID-19 pandemic, offering a rich context for understanding how traditional macroeconomic output (GDP) either aligns with or diverges from a more holistic measure of progress such as the GPI. From 2000 to 2023, Iceland’s GDP and GPI both reflect economic growth, but the GPI’s faster rise, especially post-2015, suggests improvements to economic welfare beyond purely aggregate market-based output. The financial crisis of 2008 exposed the vulnerability of Iceland’s GDP to speculative bubbles, while the GPI’s resilience then and subsequent outperformance of GDP in the period up to 2023 highlighted the value of accounting for the costs and benefits of social and environmental factors to acquire a more multifaceted portrayal. The COVID-19 pandemic period in Iceland starkly illustrated divergent responses between GDP and the GPI. Between 2019 and 2020, GDP fell 6.0% as the tourism sector collapsed. The GPI, however, rose 1.3% over the same period, buoyed by reduced environmental costs, leisure time gains, and

increased public spending on healthcare and education, even as unemployment costs surged, which offset some of the benefits.

The pandemic period and Icelandic case also offer some possible insights into potential post-growth trajectories, albeit they were largely unplanned in Iceland and reactive to an unforeseen crisis. GDP's 2020 decline mirrors constrained consumption in a degrowth scenario, while the GPI's greater resilience aligns with the emphasis placed on post-growth visions of reduced environmental costs, including large-scale reductions in non-renewable resources. Generous welfare support, which was evident in increased public expenditures on healthcare and education, echoes the emphasis of post-growth narratives on social foundations. However, spiralling unemployment costs in the GPI highlight some of the trade-offs, as economic inactivity offset environmental gains.

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Appendix

TABLE A1 Sub-Indicators Used in the Calculation of Iceland's GPI

Sub-indicator	Summary of calculation method (sources are Statistics Iceland unless stated)	Addition / deduction
Household budget expenditures (HBE) and defensive and regrettable expenditures (DEFER)	Household final consumption expenditure (HFCE).	Addition
Insurance	Derived from itemised HFCE.	Deduction
Welfare neutral goods	Derived from itemised HFCE. Followed the assumption of Lawn (2013) that 25% of alcohol consumption and 80% of tobacco and narcotics consumption were purchases likely to be welfare declining.	Deduction
Costs of maintaining dwelling services	Derived from itemised HFCE – water infrastructure and other dwelling services, e.g. waste.	Deduction
Consumer durables	Aggregated value of purchases of cars, houses, and appliances in HFCE from previous five years multiplied by 0.2 as per approach of Kenny et al. (2019).	Deduction
Household repairs and maintenance	Derived from itemised HFCE.	Deduction
Income inequality adjustment (INQ)	Index-derived adjustment based on extent of the Gini coefficient deviation from baseline – lowest year of income inequality (2014) given a base value of 100.	Deduction
Education	Itemised expenditure by central government in GDP calculation.	Addition
Healthcare	Itemised expenditure by central government in GDP calculation.	Addition
Local government services	Itemised expenditure by local government in GDP calculation, relating to health, education, recreation, social protection, housing and community amenities, environmental protection, public order and safety, defence, and other public services.	Addition
External benefits from higher education	Benefit transfer approach – annual number of Icelandic college graduates (ISCED (2011) Levels 5–8) multiplied by annual social payoff as per Talberth et al. (2007) study.	Addition
Value of leisure time	To calculate the measure for leisure time, the method applied by Talberth et al. (2007) was utilised, leading to an imaginary base year with mean leisure time of 1,770 hours per person (derived by assuming a 40-hour work week and five weeks of annual vacation time for a total of 235 working days). Adjusted mean leisure time per person was multiplied by the total number of workers in the labour force to arrive at a total number of leisure hours for the nation per annum, which was multiplied by the mean gross hourly wage rate in the private sector.	Addition

Sub-indicator	Summary of calculation method (sources are Statistics Iceland unless stated)	Addition / deduction
Value of unpaid labour in the volunteering sector	Although data is limited for Iceland, the most recent completed study of the World Values Survey, Wave 4 (Inglehart et al., 2014), estimated that 29% of Icelanders took part in voluntary work in 2014. Scaled to the Icelandic population and assuming mean volunteering hours of 89 per volunteer per year in line with the US national estimate of 2018, the total number of Icelandic volunteering hours was multiplied by the mean gross hourly wage rate in the private sector.	Addition
Value of transportation infrastructure	Aggregated annual government expenditures in GDP on road, water and air transportation, infrastructure, and maintenance.	Addition
Value of energy and water infrastructure	Aggregated annual government expenditures in GDP on electricity, non-electric energy generation and the water supply.	Addition
Waste treatment by sewer infrastructure	Aggregated annual government expenditures in GDP on waste and water waste management.	Addition
Housing development	Aggregated annual government expenditures in GDP on housing development.	Addition
Construction	Aggregated annual government expenditures in GDP on construction.	Addition
Non-renewable resource depletion	The 'transition cost' approach delineated by O'Mahony (2021) for Spain's Index of Sustainable Economic Welfare was used to approximate the costs of replacing fossil fuel consumption with renewable energy sources. An input cost of €575.99 per tonne of oil equivalent in 2010€ was used, which was equal to 139,438 ISK per tonne of oil equivalent in 2023 prices.	Deduction
Avoided depletion	Avoided depletion costs approximated by annual government expenditure in GDP on protection of biodiversity and landscape.	Deduction
Air pollution	Mortality and welfare cost of exposure to fine particulates. Estimated to be 0.42 % of Icelandic GDP per annum.	Deduction
Climate change contribution	Quantity of man-made greenhouse gas emissions multiplied by the estimated social cost of carbon of \$185/tonne by Rennert et al. (2022), which was equal to 27,481 ISK per tonne in 2023 prices.	Deduction
Solid waste	Volume in tonnes of total waste generation multiplied by external cost of Icelandic waste generation in the study of Kinnaman (2009), which was 3,288 ISK per tonne in 2023 Icelandic prices.	Deduction

Sub-indicator	Summary of calculation method (sources are Statistics Iceland unless stated)	Addition / deduction
Unemployment	Total unprovided hours of individuals aged 16–74 multiplied by gross mean private sector wage (ISK/hr).	Deduction
Crime	Total annual government cost of operating prisons and law courts in Iceland.	Deduction
Commuting	Aggregation of the direct cost of commuting, indirect time spent commuting to work, and direct costs of public transportation. Commuting cost calculated by multiplying annual commuting distance by cost of driving per km and the number of vehicles owned by households. Cost per one km of driving was calculated through the calculation of average cost of fuel per km in Iceland (Global Petrol Prices, 2024). The indirect cost of commuting times was obtained by the approximate amount of time spent reaching work multiplied by the mean gross hourly wage for full-time work in the private sector.	Deduction
Vehicle accidents	The approach of Kubiszewski et al. (2015) was followed, whereby the cost of vehicle accidents equalled number of deaths (Samgöngusófa, 2024) multiplied by cost per accident. The road administration conducted a study in 2013 on the cost of deaths in a car accident (Sigþórsson and Hilmarrsson 2014), which calculated not only individual cost, but also reflected the social cost of an accident to arrive at an estimated VSL.	Deduction

SOURCE Adapted from Cook and Davíðsdóttir (2021)

TABLE A.2 GPI Calculation Breakdown (all values in million ISK, 2023 prices)

		Household consumption and inequality				Defensive and Household Investments (HI)		Public provision of services (pP)		
CPI Inflation (indexed to 100 for 2023)	Year	Household final consumption expenditure	Income Distribution (Index based on Gini, 2014=100)	PC adj. for Inc. Distribution	Defensive regrettable expenditures (DEFR)	Consumer durables, household repairs, maintenance and education expenses	National gov. expenditure on education	National gov. expenditure on healthcare	Local government expenditure	Market-Based Welfare (Total)
287.6	2000	1,208,711	117.27	1,030,671	48,683	106,107	56,852	166,167	239,142	1,360,842
273.4	2001	1,206,347	117.89	1,023,276	50,628	78,854	63,769	170,851	267,381	1,415,445
256.9	2002	1,186,513	118.91	997,820	51,842	73,712	66,288	188,134	279,762	1,426,417
244.2	2003	1,207,689	117.98	1,023,659	52,633	90,640	70,215	198,537	270,471	1,441,441
239.2	2004	1,310,823	106.17	1,234,676	54,465	112,469	74,322	202,677	292,829	1,647,266
231.8	2005	1,437,046	110.57	1,299,640	59,133	153,674	78,587	209,622	307,541	1,702,930
222.9	2006	1,539,310	115.86	1,328,606	63,476	149,940	81,960	212,774	358,518	1,797,654
208.9	2007	1,611,169	123.35	1,306,197	65,155	157,482	86,514	228,259	376,919	1,817,394
198.8	2008	1,636,692	120.26	1,360,913	66,331	102,627	90,838	229,891	416,258	1,957,412
176.5	2009	1,473,502	130.40	1,130,017	65,678	51,672	84,545	231,102	365,446	1,721,115
157.3	2010	1,359,899	113.22	1,201,156	60,980	48,404	76,654	209,988	327,690	1,718,873
149.3	2011	1,366,198	103.96	1,314,097	62,241	57,052	76,575	207,076	328,817	1,811,821
143.5	2012	1,415,749	105.73	1,339,062	63,861	68,125	77,908	211,902	336,356	1,840,392
136.4	2013	1,410,337	105.73	1,333,944	62,422	66,535	79,117	222,360	345,437	1,858,886
131.3	2014	1,432,148	100.00	1,432,148	62,214	75,054	78,610	228,622	359,526	1,961,639
128.7	2015	1,477,971	109.25	1,352,820	63,166	93,512	83,318	234,427	374,649	1,901,804
126.7	2016	1,568,257	106.17	1,477,155	67,207	110,740	87,437	261,615	393,958	2,052,556
124.6	2017	1,648,829	113.22	1,456,358	68,704	120,228	92,602	279,651	460,948	2,122,682
122.5	2018	1,751,974	106.17	1,650,200	71,228	115,013	91,430	304,169	469,075	2,339,451

Household consumption and inequality				Defensive and Household Investments regrettable expenditures (HI)		Public provision of services (pp)		
CPI Inflation Index (2023)	Year	Household final consumption expenditure	Income Distribution (Index based on Gini, 2014=100)	PC adj. for Inc. Distribution	Defensive regrettable costs	Consumer durables, household repairs, maintenance and education expenses	National govt. expenditure on healthcare	Local Market-Based Welfare (Total)
119.3	2019	1,811,091	106.61	1,698,834	72,518	98,877	314,521	2,426,725
115.8	2020	1,815,393	109.25	1,661,670	75,777	101,789	309,460	2,421,840
112.5	2021	2,012,280	107.49	1,872,080	76,392	119,454	335,358	2,664,229
107.8	2022	2,328,230	106.61	2,183,918	74,717	138,794	347,097	3,016,713
100.0	2023	2,553,453	107.05	2,385,325	71,194	133,922	351,954	3,241,815

TABLE A.2 GPI Calculation Breakdown (all values in million ISK, 2023 prices) – Continuation

Year	Services from capital assets (KH, KS, KB & KN)				POL	SOC	Cost of pollution economic activity	Cost of Environmental and social costs (Total)	Total GPI	GDP	National population (Number)	GPI per capita	GDP per capita
	Social capital	Built capital	Human capital	Services from Capital Assets (Total)	Depletion of natural capital								
2000	947,560	52,053	5,220	1,004,833	117,487	124,954	235,514	477,955	1,887,719	2,040,697	279,049	6.76	7.31
2001	1,012,611	59,142	5,875	1,077,628	109,873	122,803	225,523	458,199	2,034,874	2,193,345	283,361	7.18	7.74
2002	1,000,440	56,012	6,264	1,062,717	114,519	125,465	227,647	467,632	2,021,502	2,194,286	286,575	7.05	7.66
2003	1,056,070	61,140	7,219	1,124,429	113,064	124,270	193,034	430,368	2,135,502	2,140,982	288,471	7.40	7.42
2004	1,101,602	61,484	8,150	1,171,236	119,550	127,998	214,804	462,351	2,356,152	2,321,247	290,570	8.11	7.99
2005	1,315,939	58,824	8,427	1,383,189	115,410	124,502	244,446	484,357	2,601,762	2,460,390	293,577	8.86	8.38
2006	1,482,872	66,946	9,742	1,559,561	121,573	141,356	279,198	542,127	2,815,088	2,731,876	299,891	9.39	9.11
2007	1,621,016	67,267	10,175	1,698,458	127,309	150,504	259,115	536,929	2,978,923	2,897,202	307,672	9.68	9.42
2008	1,680,089	88,118	10,625	1,778,832	117,454	162,772	263,425	543,651	3,192,592	3,159,380	315,459	10.12	10.02
2009	1,341,147	74,258	9,904	1,425,309	109,368	151,815	218,409	479,592	2,666,832	2,870,743	319,368	8.35	8.99
2010	1,118,842	55,271	11,784	1,185,897	106,373	148,559	186,579	441,511	2,463,259	2,644,497	317,630	7.76	8.33
2011	1,113,118	51,622	12,381	1,177,121	105,312	142,681	183,777	431,770	2,557,171	2,634,452	318,452	8.03	8.27
2012	1,333,319	51,313	11,761	1,396,393	104,327	142,726	191,330	438,383	2,798,403	2,648,174	319,575	8.76	8.29
2013	1,410,716	46,973	11,536	1,469,225	110,768	143,137	193,122	447,027	2,881,084	2,687,673	321,857	8.95	8.35
2014	1,379,737	47,515	12,303	1,439,555	110,722	142,964	176,098	429,784	2,971,410	2,739,391	325,671	9.12	8.41
2015	1,476,895	49,816	12,649	1,539,360	121,293	146,074	177,886	445,253	2,995,911	2,974,755	329,100	9.10	9.04
2016	1,627,469	58,681	13,174	1,699,324	133,491	146,426	186,734	466,651	3,285,230	3,182,774	332,529	9.88	9.57
2017	1,780,148	63,619	12,926	1,856,693	147,514	149,789	183,229	480,532	3,498,842	3,291,353	338,349	10.34	9.73
2018	1,853,974	78,208	12,632	1,944,814	157,467	152,718	196,226	506,411	3,777,854	3,483,967	348,450	10.84	10.00
2019	1,870,435	71,468	12,603	1,954,506	138,709	150,178	209,247	498,134	3,883,097	3,609,532	356,991	10.88	10.11
2020	1,906,200	77,587	13,018	1,996,805	82,491	141,978	262,193	486,661	3,931,984	3,392,266	364,134	10.80	9.32
2021	1,999,238	84,093	15,031	2,098,363	82,425	147,107	259,899	489,431	4,273,161	3,690,776	368,792	11.59	10.01
2022	2,156,018	80,820	15,741	2,252,578	82,065	148,903	223,507	454,475	4,814,816	4,380,092	376,248	12.80	11.64
2023	2,255,965	85,583	15,741	2,357,289	82,566	150,931	221,819	455,316	5,143,788	4,862,942	387,758	13.27	12.54

AI Competencies in Determining AI Adaptation among the Communication Professionals in Oman

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AI technologies and competencies are changing work patterns across organizations. Therefore, professionals need to adapt to AI-driven organizational communication practices. In this study, we explored AI competencies among communication professionals in Oman. This study aligns with the role of AI adaptation within Oman Vision 2040. We conducted a survey of 247 communication professionals from the Education, Banking, Telecom, Business, and Construction sectors. We developed scales to measure three major AI Competencies: AI Knowledge, Digital Skills, and Critical Thinking, and empirically examined them using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings revealed that AI Knowledge (KN) and Critical Thinking (CT) are strong predictors of AI attitude (AT). Moreover, AT is a strong direct predictor of AI Adaptation (AD). Therefore, the study suggests constructive policies aligned with the Digital Transformation goals of Oman Vision 2040 to promote AI knowledge and develop the critical thinking skills of Omani professionals.

Keywords: AI competencies, AI adaptation, critical thinking, digital skills, Oman Vision 2040, communication professionals

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Introduction

Global professionalism is subject to a radical transformation driven by Artificial Intelligence (AI), a pioneering technology of the Fourth Industrial Revolution. It has transitioned from a theoretical discipline to

contemporary business models (Nascimento and Meirelles 2022; Onnen 2024). AI shifts organizational flexibility and adaptation, with the potential to enhance operational efficiency, reduce costs, and facilitate data-driven decision-making (Apostoaie et al. 2025; Eltayib 2024). However, the successful integration of AI is not merely a technical challenge but depends upon the competencies of the human workforce (Baki et al. 2023; Santana and Díaz-Fernández 2023). In the Sultanate of Oman, this transition is framed within the Oman Vision 2040. The Oman focuses on digital transformation and human resource development to ensure national competitiveness (Oman Vision 2040 Implementation Follow-up Unit 2020; Pervez et al. 2025).

Oman Vision 2040 is Oman's national strategic framework for addressing developmental challenges and keeping pace with global changes (Czornik 2025; Oman Vision 2040 Implementation Follow-up Unit 2020). A primary goal of digital transformation is to make AI a significant contributor to Oman's national GDP (Tyagi et al. 2025). Oman's vision aims to improve Oman's standing among the world's developed countries by transitioning the country from a resource-dependent economy to an innovation- and knowledge-based economy (Oman Vision 2040 Implementation Follow-up Unit 2020). The key part of the vision is Human Resource Development (HRD), which emphasizes nurturing national talent with dynamic, globally competitive skills (Ayed 2022; Pervez et al. 2025). Consequently, the development of AI competencies among Omani professionals is not merely a localized requirement but a strategic necessity aligned with Oman's national priorities for a knowledge-based society (Al-Ansi et al. 2024; Pervez et al. 2025).

Within this strategic framework, communication professionals occupy an important position. They encompass a large variety of knowledge and expertise in marketing, public relations, and telecommunications. The telecommunications sector is one of the major stakeholders that provide a primary environment for the application of AI-driven revolution (Eltayib 2024). In modern AI communication environments, AI-driven tools such as chatbots and virtual assistants enable professionals to manage massive informational complexity (Eltayib 2024; Rengasamy et al. 2025). Despite the advantages of AI, many organizations in Oman continue to rely on traditional approaches. However, a significant proportion of firms in Oman are struggling to leverage AI investments to generate real value (Mikalef et al. 2023; Tyagi et al. 2025).

Between traditional and AI-driven approaches, there is a gap in the effective integration of new technologies, known as the ‘adaptation gap’. This adaptation gap is frequently attributed to a lack of clear understanding of AI’s capabilities and to a shortage of the specialized AI competencies required to navigate digital transformation (Mikalef et al. 2023; Santana and Díaz-Fernández 2023). To address this gap between AI competencies and AI adaptation, this study investigates the role of AI competencies for AI adaptation among communication professionals in Oman.

AI competencies encompass practical proficiency to engage with AI systems in the real world (Chiu 2025; Laupichler et al. 2023). Therefore, communication professionals require competencies in technological, cognitive, social, and emotional skills (Baki et al. 2023). From a technological perspective, higher-order technical skills and AI-powered systems become complementary for professionals (Baki et al. 2023; Tyagi et al. 2025). However, while AI excels at pattern recognition, human judgment remains essential for final decision-making. On the cognitive side, the ability to engage in critical thinking is paramount (Baki et al. 2023; Psyché et al. 2023).

The social and emotional dimensions of AI competency support AI adaptation. In the meantime, the demand for human-centric skills such as leadership is expected to grow significantly (Baki et al. 2023; Onnen 2024). Communication professionals serve as the interface between the organization and its stakeholders and demonstrate adaptive agility in managing psychological resistance within the organizational workforce toward AI adaptation (Baki et al. 2023; Song et al. 2025). It is argued that high levels of self-efficacy can empower Omani professionals to overcome technical and organizational challenges associated with AI adaptation. Hence, they can also catalyze the adaptation of innovative initiatives that align with Vision 2040’s sustainability goals (Abdelfattah et al. 2025).

Moreover, the business environment and management structure significantly influence AI investment and adaptation in Oman, a process that involves factors such as the perceived relative advantage and compatibility of AI innovations (Al-Haji and Bakar 2024; Klopčič et al. 2020). Furthermore, existing organizational practices play an important role in technology acceptance and adaptation in Oman (Al-Haji and Bakar 2024; Badghish and Soomro 2024), and government support through policy reforms is decisive in facilitating this transition. Funding opportunities for digital infrastructure and specialized training are part of AI transformation goals in Oman (Al-Haji and Bakar 2024; Pervez et al. 2025). The cur-

rent literature on AI adaptation focuses on the specific competency needs of communication professionals (Eltayib 2024; Tyagi et al. 2025), and on the other hand, Oman Vision 2040 provides a clear roadmap for AI adaptation in Oman, which provides the actual mechanisms that enhance successful organizational AI adaptation (Al-Ansi et al. 2024; Czornik 2025).

This study addresses the knowledge gap regarding the role of AI competencies in the AI adaptation process among communication professionals in Oman. The study highlights the nexus between technological readiness and psychological factors, such as self-efficacy and risk perception. While previous research focuses on how Omani enterprises can achieve sustainable business performance (Abdelfattah et al. 2025; Badghish and Soomro 2024), the present study aims to offer actionable insights for policymakers and industry leaders seeking to align the digital transformation of the Omani workforce with the strategic goals of Oman Vision 2040.

The following are the objectives of the study: to explore AI competencies among Omani communication professionals and to empirically measure the relationship between these competencies and their adaptation to AI. Based on the discussed objective, this study makes three key contributions. First, it develops a cognitive–attitudinal pathway which links AI competencies to AI adaptation. Second, it provides empirical evidence from Oman using a multivariate statistical approach, Partial Least Squares Structural Equation Modelling (PLS-SEM). Third, it offers policy-relevant insights aligned with Oman Vision 2040 and emphasizes cognitive competencies rather than technical training.

The organization of this paper is as follows. The second section provides insights into literature reviews related to AI competencies. The third section outlines the theoretical framework, while the fourth section presents the study's methodology. The fifth section presents the results and discussion, including an empirical analysis. Finally, the sixth section offers a conclusion and policy implications of the study along with directions for future research.

Literature Review

AI ADAPTATION AND OMAN VISION 2040

The strategic mandates of Oman Vision 2040 drive AI within the Sultanate of Oman. This mandate serves as the nation's primary roadmap, focusing on innovation and knowledge (Oman Vision 2040 Implemen-

tation Follow-up Unit 2020). One of Oman's strategic goals is to increase AI's contribution to 10% of national GDP (Pervez et al. 2025). This is one part of a strategic shift designed to overcome developmental challenges in the modern AI landscape and ensure that Oman keeps pace with rapid global changes (Czornik 2025). Within this paradigm, AI adaptation is viewed as a critical mechanism for achieving economic diversification, and the integration of AI is essential to maintain competitiveness (Al-Ajmi et al. 2025).

In Oman, studies indicate that AI adaptation has the potential to impact various economic sectors. These sectors include hydrocarbons, telecommunications, and banking. In the hydrocarbon industry, AI technologies are widely used and offer multiple advantages, including enhanced decision-making, reduced operational costs, and improved effectiveness (Al-Haji and Bakar 2024). Similarly, the telecommunications sector provides comprehensive insights for an ideal environment for AI-driven management. Numerous AI tools are enabling professionals to manage information complexity and deliver personalized customer experiences (Eltayib 2024; Antončič and Zorn 2004). Additionally, in the banking sector, AI adaptation supports fraud detection, risk management, and round-the-clock customer service, aligning with international practices (Rengasamy et al. 2025). Other than the corporate sector, AI technologies are also playing a role in the development of small and medium-sized enterprises (SMEs) in Oman. Therefore, Vision 2040 necessitates a robust focus on Human Resource Development and on empowering SMEs through the effective implementation of AI competencies (Al-Ansi et al. 2024; Tyagi et al. 2025). However, previous research indicates that while SMEs contribute to job creation and economic diversification, an 'adaptation gap' remains due to limited digital infrastructure and a shortage of specialized AI skills (Ayed 2022). This gap requires efforts to promote technical and cognitive skills and a culture of AI adaptation among Omani leaders and professionals (Abdelfattah et al. 2025).

AI COMPETENCIES AND AI ADAPTATION

The integration of AI literacy and competencies into organizations ensures successful technological adaptation (Chee et al. 2025). AI literacy provides the conceptual understanding of intelligent systems, and AI competency refers to the practical capacity to use tools in specialized professional contexts (Psyché et al. 2023). Empirical evidence suggests that a high level of AI knowledge is a primary driver of adaptation in-

tention to AI (Apostoaie et al. 2025). Conversely, a lack of fundamental understanding remains a pervasive social barrier, leading to unrealistic expectations or psychological resistance to AI adaptation (Cubric 2020; Nascimento and Meirelles 2022).

In theoretical conceptualization, AI competency is considered a multidimensional construct, with machine learning and data analytics as essential components (Ng et al. 2023). Further, scholars emphasize that 'hard' skills are insufficient without 'soft' competencies such as critical thinking and ethical judgment (Baki et al. 2023; Onnen 2024). For instance, the ability to evaluate AI-generated outputs is important to maintaining organizational trust (Ikwu and Ifediorah 2025; Song et al. 2025). Furthermore, the demand for human-centric skills is projected to grow significantly. These skills include leadership, empathy, and social intelligence. These are beyond the current capabilities of automated agents (Myszak and Filina-Dawidowicz 2025).

Organizational adaptation of AI technologies is contingent upon Human Resource Development (Hassan 2025). Research indicates that the successful implementation of AI models depends on an organization's internal readiness, which is characterized by a skilled workforce and proactive management (Badghish and Soomro 2024). In many instances, the 'adaptation gap' in SMEs is attributed to a critical deficit in digital skills. It may also be because of limited access to formal training (Popa et al. 2025). To mitigate these barriers, previous research suggests that organizational leaders must promote a culture of continuous learning and innovation. They need to encourage employees to engage in upskilling programmes. These programmes must align with professional capabilities of the Fourth Industrial Revolution and AI transformation (Myszak and Filina-Dawidowicz 2025). AI adaptation is not a one-time event but a dynamic process that provides individuals and organizations with a platform where professionals can consistently recalibrate their skills and leverage the potential of human-AI collaboration (Psyché et al. 2023).

Despite the growing body of literature on AI and digital transformation, several limitations remain. First, most studies focus on technology adoption frameworks, while giving limited attention to AI adaptation processes. AI adaptation is characterized by the effective integration and sustained use of AI in real-world socio-economic contexts. Second, existing research often examines technological competencies in isolation without considering the relationships among AI knowledge, digital skills, and higher-order cognitive abilities such as critical thinking. Third, empiri-

cal evidence from developing or transitional economies remains scarce, limiting the generalizability of existing research findings. Therefore, the present study addresses these gaps by proposing a comprehensive framework that integrates technological competencies and cognitive factors, and it contributes both theoretically and in context to the literature.

Theoretical and Conceptual Framework

AI KNOWLEDGE (KN)

AI knowledge (KN) is a cognitive competency that goes beyond basic digital literacy. It encompasses a conceptual and technical understanding of artificial intelligence (Ng et al. 2021). It involves foundational principles, such as machine learning (ML) and natural language processing (NLP), and distinguishes general and narrow AI systems (Long and Magerko 2020). KN is a framework for technological pedagogical content knowledge (TPACK) and is often categorized as content knowledge, addressing the essential role of data quality in AI systems' information processing (Kim and Kwon 2023). This competency allows professionals to interpret the 'black box' nature of AI, making it easier to understand how these systems function and make decisions (Laupichler et al. 2023).

The role of KN in AI adaptation (AD) is decisive. Both serve as critical functions in a psychological context (Popa et al. 2025; Song et al. 2025). Higher proficiency with AI concepts reduces user uncertainty and anxiety and creates a 'self-reflective mindset' that empowers individuals to integrate AI tools into their professional workflows (Baki et al. 2023). In the context of the Technology Acceptance Model (TAM), KN significantly enhances the perceived value of technological interventions (Baroni et al. 2022). This knowledge base provides the necessary scaffolding for 'Critical Appraisal' and enables users to evaluate AI-generated outputs to support sustainable human-AI collaboration (Annasureddy et al. 2025; Russell et al. 2023).

CRITICAL THINKING (CT)

CT is a higher-order cognitive AI competency that involves analyzing complex information. It deals with relevant insights and translates them into well-reasoned professional actions (Myszak and Filina-Dawidowicz 2025). Within the 'TUCAPA' framework, CT serves as the 'Critical Appraisal' dimension, generating user-friendly AI outputs on accuracy, algorithmic biases, and appropriateness (Laupichler et al. 2023). Unlike

KN, CT competency requires a self-reflective mindset focused on conceptual awareness (Annapureddy et al. 2025; Chiu 2025).

The role of CT in AI adaptation acts as a bridge between technological readiness and institutional integration. AI adaptation is not merely a matter of technical mastery, but also mitigates the risks of over-reliance on automated systems. Therefore, CT serves as a navigation tool for the ‘personalization-privacy paradox’ (Long and Magerko 2020; Popa et al. 2025). Previous research suggests that organizations can strategically delegate tasks to professionals with critical-thinking skills, which are essential to maintaining human agency while enabling enhanced decision-making. (Baroni et al. 2022; Song et al. 2025). CT also plays an important role in ensuring that AI adaptation remains sustainable and compatible with a knowledge-based economy (Santana and Díaz-Fernández 2023; Zhou et al. 2025).

DIGITAL SKILLS (DS)

Digital skills constitute a foundational dimension of AI competency. Both the basic and higher-order technical proficiencies are required for professional landscape (Baki et al. 2023; Onnen 2024). This DS competency is a prerequisite for AI literacy, which involves the ability to use AI-powered hardware and software platforms. In addition, DS also manages the digital infrastructure necessary for AI systems (Chiu 2025; Long and Magerko 2020). Beyond traditional computer literacy, digital skills in the AI era involve specialized competencies in forms such as the ability to troubleshoot algorithmic systems, interpret digital outputs, and ensure data security (Baki et al. 2023; Onnen 2024). DS enables the systematic implementation of new technologies and transforms passive consumers into active interpreters, leading toward organizational workflows and work culture (Santana and Díaz-Fernández 2023; Song et al. 2025).

The role of DS serves as a psychological mitigator. Empirical evidence indicates that a lack of specialized digital expertise remains a barrier to AI adaptation, creating an adaptation gap that leaves AI investments under-leveraged (Apostoaie et al. 2025; Mikalef et al. 2023). Conversely, higher levels of digital competency enhance self-efficacy and reduce cognitive load among working professionals experiencing AI anxiety and fear (Hassan 2025; Popa et al. 2025). The technical ‘know-how’ regarding the AI capabilities with DS is necessary to facilitate the integration of digital tools (Badghish and Soomro 2024; Santana and Díaz-Fernández 2023).

Therefore, DS bridges the gap between human intelligence and machine processing (Myszak and Filina-Dawidowicz 2025; Onnen 2024).

AI ATTITUDE (AT)

A central cognitive construct of our study, AT determines an individual's internal evaluation and sensemaking of AI systems (Hassan 2025; Song et al. 2025). It has been studied using two models: the Technology Acceptance Model (TAM) and the Attitude Towards Use (ATU). Both models represent the extent to which positive or negative professional feelings affect the specific behaviour of integrating AI into workflows (Hassan 2025). In TAM, AT is related to perceived usefulness and perceived ease of use (Hassan 2025; Marikyan and Papagiannidis 2022), which encompass broader psychological factors, such as the perceived usefulness and ease of use of AI technologies (Baroni et al. 2022; Popa et al. 2025). Furthermore, AT is deeply linked to 'affective competencies', including the individual's interest and self-reflective mindset. Aligning AI with evolving societal and professional standards is also part of these affective competencies (Chee et al. 2025; Ng et al. 2021).

AT represents a behavioural intention to engage in AI adaptation in real-world contexts (Hassan 2025; Song et al. 2025), which is facilitated by lowered psychological barriers and reduced technology-related anxiety (Song et al. 2025; Tambe et al. 2019). Professionals willing to engage in 'human-in-the-loop' can actively contribute to AI adaptation (Baroni et al. 2022; Popa et al. 2025). Conversely, a negative attitude leads to an 'adaptation gap' which may be caused by the fears of job displacement or high perceived risk (Hassan 2025; Lada et al. 2023). Therefore, to promote an innovation-friendly culture, a positive attitude is necessary for AI adaptation in organizations (Popa et al. 2025; Song et al. 2025).

AI ADAPTATION (AD)

Integrating AI and intelligent agents within an organization is considered AD. It enhances operational efficiency and sustains organizational growth (Apostoaie et al. 2025; Mikalef et al. 2023). AD is also compatible with the Technology-Organization-Environment (TOE) framework, which suggests that successful institutionalization depends on the interplay between a firm's technological readiness and external environmental pressures (Apostoaie et al. 2025; Badghish and Soomro 2024). Adaptation represents a dynamic evolution rather than a static implementation and is considered a pivotal component of contemporary business mod-

els, reconfiguring workflows, resource allocation, and traditional labour relations (Mikalef et al. 2023; Santana and Díaz-Fernández 2023). In response to volatile market conditions, AD can optimize decision-making and reduce human workload (Apostoaie et al. 2025; Song et al. 2025).

The successful adaptation to AI in organizations represents a significant shift toward a culture of continuous learning and collaborative intelligence (Baki et al. 2023; Myszak and Filina-Dawidowicz 2025). This adaptation requires individuals to move beyond merely using passive tools and to integrate their cognitive skills with machine efficiency (Baroni et al. 2022). On the other hand, the ‘adaptation gap’ can complicate the development of essential AI competencies among professionals (Baki et al. 2023; Santana and Díaz-Fernández 2023). Therefore, adaptation leads to changes in the professional attitudes of the workforce (Baroni et al. 2022; Popa et al. 2025) and, in turn, transforms technological potential into a lasting competitive advantage in organizations (Apostoaie et al. 2025; Badghish and Soomro 2024).

HYPOTHESES AND CONCEPTUAL MODEL OF THE STUDY

Based on the theoretical discussion, this study assesses the extent of AI technology adaptation in professional practice. It is based upon the Technology Acceptance Model (TAM) and competency-based perspectives of AI literacy. The following hypotheses are therefore developed to empirically test these relationships.

AI knowledge can strengthen professionals’ ability to critically evaluate AI technologies and their implications. Thus, AI knowledge becomes a fundamental component of AI competency. Professionals with knowledge of AI technologies are better equipped to evaluate algorithmic processes and assess the reliability of AI-generated outputs. Meanwhile, digital skills interact with digital technologies and AI tools in professional settings. Individuals with strong digital skills are better equipped to explore AI applications. It is hypothesized that professionals with higher levels of digital skills are more likely to develop stronger critical thinking regarding AI technologies.

H1A AI Knowledge will be more likely to influence critical thinking among communication professionals.

H1B Digital Skills will be more likely to influence critical thinking among communication professionals.

For developing hypotheses, it is assumed that critical thinking shapes individuals' perceptions and attitudes toward emerging technologies. Professionals with strong analytical and evaluative abilities can effectively assess the opportunities and risks associated with AI systems. This leads to greater trust and confidence in AI technologies, rather than relying on emotional reactions such as anxiety and fear. It can be stated that critical thinking promotes balanced attitudes toward AI adaptation. Therefore, we hypothesize H2 as follows:

H2 Critical Thinking will be more likely to influence AI Attitude among communication professionals.

Attitude toward technology determines behavioral intention in the TAM. Individuals who hold positive attitudes toward AI are more willing to integrate AI tools into their professional tasks. This leads to a favourable perception of AI, thereby reducing psychological resistance to AI adaptation while encouraging experimentation with AI-driven systems. Therefore, hypothesis H3 is based on the assumption that professionals with positive attitudes toward AI are more likely to adapt effectively to AI technologies.

H3 AI Attitude will be more likely to predict AI adaptation among communication professionals.

Methodology

The present study is based on a quantitative survey methodology. Data collection is purposive, where 247 communication professionals were selected from Oman. All the respondents were approached through a referral sampling strategy. A research questionnaire was developed in Google Forms and shared with the target participants. In the questionnaire, we developed five scales concerning AI Competencies and Adaptation (table 1). All the ethical guidelines were followed, and data were collected after formal institutional ethical approval.

The selection of communication professionals is justified both theoretically and contextually. Communication professionals occupy a strategic position, responsible for managing information flows and digital engagement. In the context of AI, their role becomes critical as they interact directly with AI-enabled tools. This makes them particularly suitable for examining AI competencies and adaptation processes. Furthermore, the selection is aligned with the national priorities of Oman Vision 2040. By

TABLE 1 Scales and Measures of Study

Scale Name	Item Code	Statement
AI Adaptation (AD)	AD1	I am familiar with Generative AI tools (i.e., ChatGPT, Gemini, Online Translators, Work Automation, etc.).
	AD2	I often use GenAI (i.e. ChatGPT, Gemini, etc.) in my workplace.
	AD3	I am confident in my ability to use and interact with GenAI applications.
	AD4	I am comfortable with GenAI applications being part of my daily life.
	AD5	I enjoy using GenAI applications for various professional purposes.
AI Knowledge (KN)	KN1	I can define and explain what GenAI (i.e. ChatGPT, Gemini, etc.) is and how it works.
	KN2	I know the different types of GenAI applications and their features and functions.
	KN3	I can understand the benefits and limitations of GenAI for various domains and professional tasks.
	KN4	I can understand and recognize the common applications and examples of GenAI (i.e. ChatGPT and Gemini) in everyday life, such as voice assistants, social media analytics, online translators, etc.
	KN5	I can assess the accuracy and quality of AI applications and their outputs, such as predictions, recommendations, classifications, etc.
Digital Skills (DS)	DS1	I can use GenAI (i.e. ChatGPT, Gemini, etc.) applications effectively and efficiently for my personal and professional needs.
	DS2	I can utilize reliable and valid GenAI applications (i.e. ChatGPT and Gemini) to achieve my professional outputs.
	DS3	I can troubleshoot and solve problems when using GenAI applications (i.e. ChatGPT and Gemini etc.).
	DS4	I can select and use appropriate data sources and formats for GenAI (i.e. ChatGPT, Gemini, etc.) applications.
	DS5	I can easily learn new digital and technological skills to achieve AI proficiency in my workplace.
	DS6	I can effectively craft prompts for GenAI applications (i.e. ChatGPT and Gemini, etc.).
AI Attitude (AT)	AT1	I am interested in learning more about GenAI and its applications.
	AT2	I am optimistic about the future of GenAI and its impact on society.
	AT3	I trust GenAI applications to perform their tasks reliably and safely.
	AT4	I appreciate the benefits and opportunities that GenAI applications offer me.

Scale Name	Item Code	Statement
Critical Thinking (CT)	AT 5	I feel responsible for using GenAI applications ethically and responsibly.
	AT 6	I respect the rights and interests of other users and stakeholders of AI applications.
	CT 1	I can critically evaluate the ethical principles and values that guide the development and use of GenAI applications (i.e. ChatGPT and Gemini, etc.) .
	CT 2	I can critically evaluate the potential risks and harms of AI applications (i.e. ChatGPT and Gemini, etc.) for individuals and groups.
	CT 3	I am aware of the legal and regulatory frameworks that govern the use of AI applications (i.e. ChatGPT and Gemini, etc.).
	CT 4	I can critically evaluate the social and cultural implications of AI applications for diversity and inclusion.
	CT 5	I am aware of the opportunities and benefits of AI applications (i.e. ChatGPT and Gemini etc.) for society and humanity.
	CT 6	I am aware of the current and future trends and developments of AI systems and their applications.

NOTE All items were measured on a five-point Likert scale.

focusing on communication professionals, the study provides policy-relevant insights into workforce readiness for AD. Thus, the sample selection makes AD multidimensional by integrating professional relevance, sectoral diversity, and national strategic alignment.

In pursuit of a self-reported survey design, procedural remedies were employed to minimize common method bias. Respondent anonymity was assured. None of the identifying information was collected to reduce evaluation apprehension. The questionnaire items were carefully structured and made clear and concise to avoid ambiguity. Furthermore, the study employed well-established, conceptually distinct constructs to reduce the likelihood that common method variance would influence the results.

Table 2 presents the descriptive statistics for all measurements. The items include AD, AT, CT, DS, and KN, based on responses from communication professionals in Oman (the details of each acronym are provided in table 1). The measures of central tendency show the overall mean and the sub-factor values. This value range between 3.06 and 3.78 indicates a moderate to moderately high level across all constructs. AI Adaptation items show variability.

The dispersion (standard deviation) ranges from 0.899 to 1.260, which is acceptable for survey-based social science research. While

TABLE 2 Descriptive Statistics

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Number of observations used	Cramér-von Mises test statistic	Cramér-von Mises <i>p</i> -value
AD2	3.061	3.000	1.000	5.000	1.260	-0.969	-0.005	247.000	1.182	0.000
AD5	3.640	4.000	1.000	5.000	1.115	-0.283	-0.593	247.000	1.747	0.000
AT2	3.595	4.000	1.000	5.000	1.075	-0.201	-0.553	247.000	1.820	0.000
AT3	3.206	3.000	1.000	5.000	1.099	-0.716	-0.178	247.000	1.561	0.000
AT4	3.470	4.000	1.000	5.000	0.934	0.114	-0.436	247.000	2.378	0.000
AT5	3.713	4.000	1.000	5.000	0.945	0.041	-0.670	247.000	3.116	0.000
AT6	3.636	4.000	1.000	5.000	0.946	0.365	-0.597	247.000	2.413	0.000
CT1	3.555	4.000	1.000	5.000	0.920	0.396	-0.507	247.000	2.489	0.000
CT2	3.498	4.000	1.000	5.000	1.041	-0.163	-0.547	247.000	2.122	0.000
CT3	3.478	4.000	1.000	5.000	0.939	-0.394	-0.231	247.000	2.153	0.000
CT4	3.522	4.000	1.000	5.000	1.083	-0.072	-0.654	247.000	2.165	0.000
CT5	3.583	4.000	1.000	5.000	0.986	0.461	-0.718	247.000	2.512	0.000
CT6	3.753	4.000	1.000	5.000	1.072	0.083	-0.684	247.000	1.876	0.000
DS1	3.781	4.000	1.000	5.000	0.914	1.076	-0.834	247.000	2.863	0.000
DS2	3.486	4.000	1.000	5.000	0.921	0.237	-0.552	247.000	2.648	0.000
DS3	3.413	4.000	1.000	5.000	0.909	0.145	-0.521	247.000	2.677	0.000
DS6	3.534	4.000	1.000	5.000	0.899	0.562	-0.693	247.000	3.071	0.000
KN2	3.255	3.000	1.000	5.000	0.920	-0.488	0.005	247.000	2.177	0.000
KN3	3.547	4.000	1.000	5.000	0.898	1.247	-0.866	247.000	3.204	0.000
KN4	3.437	4.000	1.000	5.000	0.950	-0.115	-0.603	247.000	3.016	0.000
KN5	3.356	3.000	1.000	5.000	1.007	-0.259	-0.451	247.000	2.170	0.000

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

considering the distribution shape, skewness values are predominantly negative, indicating that responses are skewed toward higher levels of agreement. This is particularly evident for two key constructs: DS and AT items. Excess kurtosis values are mostly negative or close to zero. Such distributions are typical for Likert-scale data in applied research. For Normality Assessment, the Cramér–von Mises test yields statistically significant results for all items, indicating deviations from normality.

The result is not problematic for the study because Likert-scale data are inherently ordinal. Meanwhile, a large sample size, such as $n = 247$ in this study (see demographic characteristics in table 3), increases the

TABLE 3 Demographics of the Study

	Frequency	Percent	Valid Percent	Cumulative Percent
Gender				
Male	148	59.9	59.9	59.9
Female	99	40.1	40.1	100.0
Total	247	100.0	100.0	
Profession				
Banking Sector	12	4.9	4.9	4.9
Business	24	9.7	9.7	14.6
Corporate Sector	24	9.7	9.7	24.3
Education Sector	90	36.4	36.4	60.7
Energy Sector	8	3.2	3.2	64.0
Government Services	16	6.5	6.5	70.4
Health Sector	16	6.5	6.5	76.9
Other	49	19.8	19.8	96.8
Private Job	8	3.2	3.2	100.0
Total	247	100.0	100.0	
Education				
Diploma	76	30.8	30.8	30.8
Bachelors	130	52.6	52.6	83.4
Masters	32	13.0	13.0	96.4
Doctorate	9	3.6	3.6	100.0
Total	247	100.0	100.0	

sensitivity of normality tests. This makes the data fully suitable for subsequent structural modelling.

Findings and Discussion

Table 4 presents the direct structural relationships among the latent constructs and reports standardized path coefficients, standard deviations, *t*-statistics, *p*-values, and bootstrapped confidence intervals.

AT → AD: The path from AI Attitude to AI Adaptation is strong and highly significant, with a coefficient value of 0.659. This indicates that professionals with a more positive attitude toward AI are more likely to adapt it, suggesting that AI use in professional activities is higher than usual. The model's core behavioural mechanism justifies this relationship. These results are consistent with the Technology Acceptance Model (TAM) model. TAM suggests that attitude toward use is a direct antecedent of actual technology use (Hassan 2025; Song et al. 2025). A positive

TABLE 4 Path Coefficients

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
AT → AD	0.6590	0.6603	0.0465	14.1677	0.0000
KN → CT	0.7264	0.7293	0.0541	13.4234	0.0000
CT → AT	0.7770	0.7766	0.0329	23.6162	0.0000
DS → CT	0.1070	0.1059	0.0658	1.62510	0.1041
Confidence intervals		Confidence intervals bias corrected.			
	2.5%	97.5%	Bias	2.5%	97.5%
AT → AD	0.5607	0.7435	0.0012	0.5536	0.7382
KN → CT	0.6236	0.8377	0.0029	0.6188	0.8329
CT → AT	0.7077	0.8349	−0.0003	0.7059	0.8326
DS → CT	−0.0277	0.2326	−0.0011	−0.0278	0.2323

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

attitude toward AI serves as a psychological enabler, which contributes to lower resistance and enhances willingness to institutionalize AI tools in the workplace. The magnitude of the coefficient indicates that attitudinal acceptance is not a marginal influence. However, it can be considered a behavioural mechanism that translates cognitive readiness into actual adaptation. This approach has strategic relevance for Oman Vision 2040. The vision focuses on digital transformation, innovation, and human capital development and further includes national strategies compatible with psychological readiness and cultural acceptance of AI. Thus, a positive attitude toward AI has a multiplier effect on AI adaptation (Al-Ansi et al. 2024; Hassan 2025).

KN → CT: The relationship between AI Knowledge and Critical Thinking is very strong and is statistically significant, with a coefficient of 0.726. This demonstrates that AI knowledge significantly enhances professionals’ ability to evaluate various externalities critically. These externalities include ethical, social, and practical implications of AI, as discussed in hypothesis H1a. The finding is aligned with contemporary AI literacy and competency frameworks. CT is considered an advanced stage of AI competency (Laupichler et al. 2023; Chiu 2025). This stage emerges after foundational knowledge. The phrase suits in this context: *one cannot critically evaluate what one does not conceptually understand*. Therefore, the KN impact on CT is particularly crucial for communication professionals. Their work directly affects public perception and ethical accountability.

CT → AT: The path from Critical Thinking to AI Attitude is the strongest in the model and significant, with a coefficient of 0.777. This direct relationship suggests that critical thinking is the primary driver of positive attitudes toward AI. This supports hypothesis H2. This path highlights that critical thinking is the central cognitive mechanism in AI adaptation. Attitudes toward technologies are formed through reflective evaluation (Chee et al. 2025; Myszak and Filina-Dawidowicz 2025) and are assessed against professional and societal norms. CT is likely to develop informed trust rather than blind acceptance. Hence, AI attitude, followed by critical thinking, is shaped by reasoned judgment and ethical awareness.

DS → CT: Digital Skills to Critical Thinking is found to be weak and not statistically significant, although the path coefficient DS → CT is positive, having a coefficient value of 0.107. This implies that digital proficiency alone does not translate into higher-order critical thinking about AI. The findings of this direct relationship lead to the rejection of H1b. This result elaborates a conceptual distinction between *‘doing AI’* and *‘thinking about AI’*. If digital skills for using AI tools cannot detect algorithmic bias or evaluate societal consequences, then mere digital skills are insufficient for meaningful critical thinking. Therefore, efficient users of AI tools who lack a critical understanding are considered at risk (Russell et al.

TABLE 5 Total Indirect Effect

Path	Original Sample mean		Standard deviation	T statistics	P values
	sample (O)	(M)	(STDEV)		
KN → AD	0.372	0.375	0.046	8.130	0.000
KN → AT	0.564	0.566	0.048	11.737	0.000
CT → AD	0.512	0.513	0.049	10.480	0.000
DS → AD	0.055	0.055	0.035	1.555	0.120
DS → AT	0.083	0.083	0.052	1.594	0.111
Confidence intervals			Confidence intervals bias corrected.		
	2.5%	97.5%	Bias	2.5%	97.5%
KN → AD	0.287	0.466	0.003	0.282	0.461
KN → AT	0.474	0.661	0.002	0.472	0.659
CT → AD	0.414	0.602	0.001	0.409	0.600
DS → AD	-0.013	0.125	0.000	-0.013	0.125
DS → AT	-0.020	0.185	0.000	-0.020	0.185

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

2023; Ayed 2022). Critical thinking requires domain-specific conceptual knowledge, enriched by ethical reasoning, rather than mere exposure or practice. Therefore, the weak relationship of $DS \rightarrow CT$ path explains why digital skills fail to exert meaningful indirect effects on AI attitude and adaptation.

Table 5 reports the total indirect effects of mediating constructs in the model. The indirect effect of AI Knowledge on AI Adaptation is positive.

$KN \rightarrow AD$: This has a coefficient value of 0.372, which is statistically significant. This indicates that AI Knowledge does not influence adaptation directly, but through mediating mechanisms. The effect is exerted entirely through both factors, CT and AT. This confirms that conceptual understanding of AI enhances adaptation only (Laupichler et al. 2023; Popa et al. 2025). It is further translated into evaluative reasoning and positive attitudinal orientation.

$KN \rightarrow AT$: AI knowledge shows a strong and significant indirect effect on AI Attitude 0.564. This demonstrates that AI Knowledge substantially shapes professionals' attitudes toward AI. The main role of CT is to mediate between KN and AT. It reflects the cognitive–affective transmission mechanism embedded in the model (Laupichler et al. 2023; Song et al. 2025).

$CT \rightarrow AD$: The indirect effect of Critical Thinking on AI Adaptation is large and highly significant at 0.512. This confirms that CT primarily affects AI adaptation through AT. AT plays a mediating role and serves as an immediate behavioural antecedent to AI adaptation (Hassan 2025; Song et al. 2025).

$DS \rightarrow AD$: A statistically non-significant relationship is found between Digital Skills and AI Adaptation. It indicates that Digital Skills do not meaningfully contribute to AI Adaptation. It is therefore verified through the proposed cognitive–attitudinal pathways.

$DS \rightarrow AT$: The indirect effect of Digital Skills on AI Attitude is also non-significant. This suggests that operational or technical proficiency alone does not contribute to AI attitude (Chee et al. 2025; Ikwu and Ifediorah 2025; Onnen 2024) unless it is accompanied by AI knowledge and critical evaluation.

The mediation results reveal a clear hierarchical mechanism in AI adaptation: *AI Knowledge* $\rightarrow$ *Critical Thinking* $\rightarrow$ *AI Attitude* $\rightarrow$ *AI Adaptation*. In conclusion, digital skills are necessary for interacting with AI tools. However, they fail to generate meaningful indirect effects on either AT or AD. This finding resonates with cognitive and evaluative compe-

TABLE 6 Specific Indirect Effects and Total Effects of AI Competencies on AI Adaptation

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
DS → CT → AT → AD	0.055	0.055	0.035	1.555	0.120
CT → AT → AD	0.512	0.513	0.049	10.480	0.000
DS → CT → AT	0.083	0.083	0.052	1.594	0.111
KN → CT → AT → AD	0.372	0.375	0.046	8.130	0.000
KN → CT → AT	0.564	0.566	0.048	11.737	0.000
Total Effect					
AT → AD	0.659	0.660	0.047	14.168	0.000
KN → AD	0.372	0.375	0.046	8.130	0.000
KN → AT	0.564	0.566	0.048	11.737	0.000
KN → CT	0.726	0.729	0.054	13.423	0.000
CT → AD	0.512	0.513	0.049	10.480	0.000
CT → AT	0.777	0.777	0.033	23.616	0.000
DS → AD	0.055	0.055	0.035	1.555	0.120
DS → AT	0.083	0.083	0.052	1.594	0.111
DS → CT	0.107	0.106	0.066	1.625	0.104

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

tencies. Critical thinking skills drive sustainable AD among communication professionals, rather than technical or digital skills alone.

Table 6 deals with both specific indirect effects and total effects. The specific effect highlights the model's cognitively driven mediating role.

The indirect path CT → AT → AD is strong and highly significant, with a value of 0.512. This implies a sequential pathway leading to cognitive–attitudinal mechanisms that drive AI adaptation. Professionals adapt to AI not because they think critically per se, but because they think critically to stay informed and maintain a positive attitude toward AI tools and technologies (Baroni et al. 2022; Laupichler et al. 2023; Popa et al. 2025). Therefore, this attitude triggers genuine adaptive behaviour.

Further, it confirms that CT affects AD primarily through AT. Likewise, the mediation KN → CT → AT → AD is statistically significant, with a value of 0.372. It indicates that knowledge contributes to adaptive behaviour only after it has been transformed into higher-order critical thinking. It is then subsequently transformed into a favourable attitude. The indirect

effect $KN \rightarrow CT \rightarrow AT$ is also large and significant, with a value of 0.564. This suggests that CT serves as a key cognitive conduit between KN and AT . In contrast, mediation paths involving DS ($DS \rightarrow CT \rightarrow AT$ and $DS \rightarrow CT \rightarrow AT \rightarrow AD$) are non-significant. This suggests that digital skills do not meaningfully trigger attitudinal or behavioural outcomes through cognitive mechanisms (Ikwa and Ifediorah 2025; Onnen 2024).

The results of total effects report the overall magnitude of relationships and therefore confirm the dominance of attitudinal and cognitive factors in the model. AT shows a strong total effect on AD , with AT considered the most proximal determinant of adaptation. CT also exhibits a substantial total effect on AD , having a coefficient value of 0.512. Critical thinking is largely operated through attitude. As CT is a distal cognitive driver rather than a proximal behaviour, it shapes the individual's thinking about evaluation, judgment, and the development of a sense of AI . CT transforms risk–benefit evaluations into informed trust and reduces irrational fear. KN demonstrates significant total effects on CT (0.726), AT (0.564), and AD (0.372). AI Knowledge is a foundational upstream competency that drives AI adaptation and serves as the channel for enhanced critical thinking and for shaping positive AI attitudes. Conversely, DS exhibits weak and non-significant total effects on CT , AT , and AD . Technical proficiency alone is insufficient to drive AI adaptation. It must be accompanied by cognitive and attitudinal development (Chee et al. 2025; Ikwa and Ifediorah 2025).

Table 7 confirms the robustness and statistical adequacy of the measurement model. Both outer loadings and outer weights for all indicators are reported. All indicators load strongly and significantly on their respective constructs. The recommended threshold for the outer loading generally exceeds 0.70. This condition is satisfactory in terms of reliability and convergent validity. For example, the AD indicators exhibit particularly high loadings (≥ 0.87). It is considered as a strong representation of the latent construct.

Other indicators, such as AT and CT , also show consistently high and significant loadings. This makes the construct measurement more coherent and well-defined, although a few indicators (e.g., AT_2 , DS_1) show relatively low loadings. However, they remain statistically significant and within acceptable limits. The literature suggests that when outer weights are positive and highly significant, it confirms that each indicator contributes meaningfully to its construct (Hair et al. 2019). However, it is essential to be considered jointly with other indicators. Notably, the bal-

TABLE 7 Measurement Model Assessment: Outer Loadings and Outer Weights

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
Outer Loading					
AD2 → AD	0.874	0.873	0.019	45.208	0.000
AD5 → AD	0.930	0.931	0.009	99.731	0.000
AT2 → AT	0.682	0.680	0.047	14.465	0.000
AT3 → AT	0.802	0.801	0.021	37.652	0.000
AT4 → AT	0.875	0.874	0.017	52.101	0.000
AT5 → AT	0.827	0.827	0.027	31.148	0.000
AT6 → AT	0.875	0.874	0.020	43.223	0.000
CT1 → CT	0.760	0.760	0.030	25.419	0.000
CT2 → CT	0.833	0.832	0.022	37.909	0.000
CT3 → CT	0.835	0.834	0.022	38.418	0.000
CT4 → CT	0.859	0.859	0.018	46.692	0.000
CT5 → CT	0.837	0.836	0.022	38.354	0.000
CT6 → CT	0.756	0.755	0.043	17.676	0.000
DS1 → DS	0.735	0.731	0.069	10.688	0.000
DS2 → DS	0.782	0.781	0.035	22.630	0.000
DS3 → DS	0.812	0.811	0.031	26.304	0.000
DS6 → DS	0.848	0.847	0.032	26.377	0.000
KN2 → KN	0.816	0.816	0.027	30.130	0.000
KN3 → KN	0.881	0.881	0.017	51.468	0.000
KN4 → KN	0.834	0.834	0.017	48.255	0.000
KN5 → KN	0.801	0.800	0.035	22.756	0.000
Outer weight					
AD2 → AD	0.475	0.474	0.023	20.413	0.000
AD5 → AD	0.629	0.629	0.025	25.052	0.000
AT2 → AT	0.210	0.210	0.013	16.451	0.000
AT3 → AT	0.241	0.241	0.009	26.394	0.000
AT4 → AT	0.272	0.273	0.013	20.246	0.000
AT5 → AT	0.253	0.253	0.010	26.495	0.000
AT6 → AT	0.247	0.247	0.009	26.384	0.000
CT1 → CT	0.210	0.210	0.009	24.639	0.000
CT2 → CT	0.205	0.205	0.008	24.942	0.000
CT3 → CT	0.197	0.197	0.009	22.785	0.000
CT4 → CT	0.204	0.204	0.009	23.226	0.000
CT5 → CT	0.217	0.217	0.011	19.012	0.000
CT6 → CT	0.197	0.197	0.010	19.367	0.000
DS1 → DS	0.263	0.263	0.043	6.159	0.000
DS2 → DS	0.269	0.268	0.032	8.426	0.000
DS3 → DS	0.360	0.359	0.024	14.872	0.000
DS6 → DS	0.358	0.358	0.033	10.751	0.000
KN2 → KN	0.295	0.295	0.013	22.466	0.000
KN3 → KN	0.349	0.349	0.015	22.564	0.000
KN4 → KN	0.316	0.317	0.014	22.052	0.000
KN5 → KN	0.235	0.235	0.015	15.444	0.000

NOTE AT: AI Attitude; AD: AD Adaptation; KN: AI Knowledge; CT: Critical Thinking; DS: Digital Skills

anced magnitude of weights suggests that no single indicator dominates construct formation. If any differentiation is found, it reflects multidimensionality within the constructs.

Figure 1 illustrates the estimated PLS-SEM structural and measurement model. Their standardized coefficients are also provided. The measurement model shows strong indicator reliability. All manifest variables load substantially on their respective latent constructs (generally ≥ 0.68). It supports the convergent validity. Additionally, the reliability and convergent validity of constructs are provided in table C in the appendix.

Table 8 shows rigorous estimation and inference settings for the PLS-SEM analysis. The algorithm employs standardized results. These results portray a path-weighting scheme, a high iteration cap (3000), and a stringent convergence criterion (10^{-7}). They are all used as benchmarks for numerical stability. Bootstrapping is configured with a two-tailed test at $\alpha = 0.05$ and parallel processing. The use of a fixed seed enhances reproducibility. On the other hand, the selected complexity setting prioritizes computational efficiency. All of this provides robust insights without compromising the quality of inference. Tables A and B in the appendix provide inner and outer model specifications and cross-loading, respectively.

Conclusion and Policy Insights

CONCLUSION AND POLICY IMPLICATIONS

This study examined how AI competencies shape AI adaptation among communication professionals in Oman. The study covers the strategic context of Oman Vision 2040. Results are presented using PLS-SEM. The findings from the empirical analysis reveal that AI adaptation is not driven by technical capability but rather follows a cognitive–attitudinal pathway anchored in knowledge and critical evaluation. AI Attitude is the most proximal and strongest predictor of AI Adaptation and is compatible with a psychological orientation toward AI. Therefore, AI attitude is the key mechanism through which professionals translate their AI readiness into actual adaptation. The literature also supports the paradox that attitudinal acceptance serves as a behavioural catalyst for the institutionalization of AI tools in professional communication practices.

At the cognitive level, Critical Thinking is the most influential upstream driver. A strong effect on AI Attitude is empirically evident, and a substantial indirect effect of critical thinking on AI adaptation is also examined,

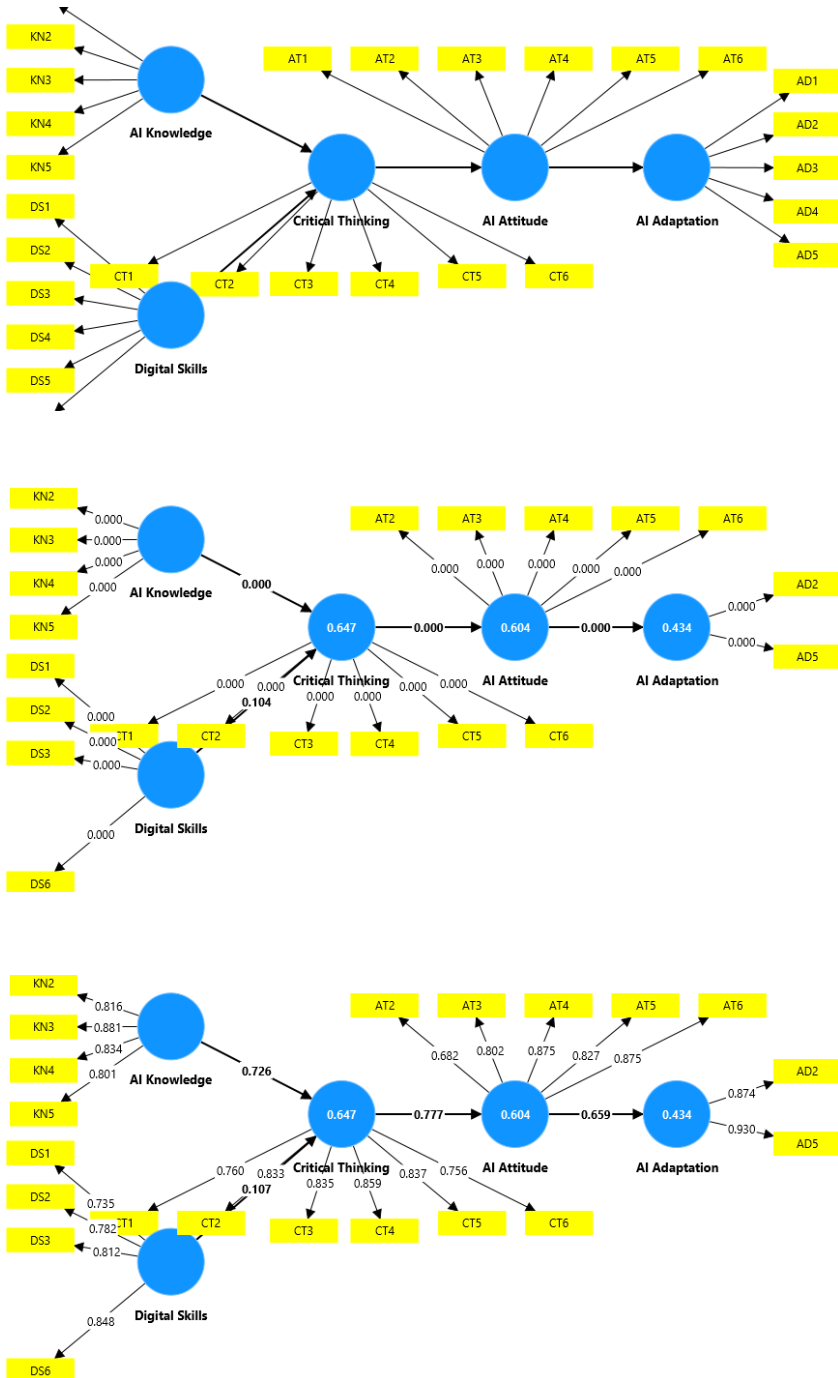


FIGURE 1 Conceptual and Empirical Visualization of AI Competencies

TABLE 8 PLS-SEM Algorithm and Bootstrapping Settings

	Setting
PLS-SEM algorithm	
Initial weights	1.0
Max. number of iterations	3000
Stop criterion	10^{-7}
Type of results	Standardized
Use Lohmoeller settings?	No
Vary copula by binary categories.	Yes
Weighting scheme	Path
Bootstrapping	
Complexity	Most important (faster)
Confidence interval method	Bias-corrected and accelerated (BCa) bootstrap
Parallel processing	Yes
Samples	5000
Save results per sample.	No
Seed	Fixed seed
Significance level	0.05
Test type	Two tailed
Coefficient of Determination (R^2)	
AD	0.75
KN	0.64
DS	0.61
AT	0.58
CT	0.54

showing that critical thinking plays a significant role in promoting positive attitudes toward AI technologies among the communication professionals in Oman. This AI attitude reflects AI's ethical, social, and professional implications. Critical thinking, therefore, operates as a *distal yet decisive force*. It is one of those cognitive mechanisms that shapes informed trust rather than blind acceptance of AI outputs. Additionally, in the adaptation process, the role of AI Knowledge is foundational. A strong empirical path from AI knowledge to critical thinking, with indirect effects on both AI Attitude and AI Adaptation, is confirmed. Thus, AI knowledge must be transformed into positive attitudes to influence behaviour.

In contrast, Digital Skills show weak and non-significant effects on Critical Thinking, AI Attitude, and AI Adaptation. Although digital proficiency is necessary to interact with AI tools, it does not, on its own, generate favourable attitudes. Therefore, there is a critical distinction between *using AI* and *understanding AI*.

To accelerate AI adaptation in line with national digital transformation agendas, several policy-relevant insights are needed. Policies should prioritize cognitive and evaluative competencies for human capital development. They should not only rely on technical training but Also Nationalize AI strategies and embed AI knowledge and critical thinking to gain greater advantages for professionals. There should be professional training programs enriched with AI-related competencies. These competencies are structured learning pathways that link AI knowledge to critical thinking and, in turn, to AI adaptation among communication professionals. Such programs can strengthen informed trust and reduce psychological resistance among communication professionals toward AI adaptation in communication technologies.

Organizations should explicitly address the attitudinal readiness of their workforce, which is one of the strongest predictors of AI adaptation and the resulting organizational change. The organizations need to take steps, including awareness campaigns, participatory AI governance, and human-in-the-loop practices. Professionals' positive attitudes toward AI promote positive perceptions of AI technologies and encourage AI adaptation. In the wake of Oman Vision 2040, it is essential to re-frame AI readiness as a behavioural and cognitive challenge. AI literacy programmes can set a milestone, while AI investments can increase organizational value. Especially, communication professionals should be positioned as AI sense-makers. They can act as intermediaries between technology, institutions, and society. They can interpret AI outputs and shape responsible public narratives around AI use.

LIMITATIONS AND FUTURE DIRECTIONS OF THE STUDY

Despite its contributions, this study has several limitations that should be acknowledged. This study is based on a cross-sectional research design. AI adaptation is dynamic, and causal inferences should therefore be interpreted with caution. The use of data-collection measurements is a form of perceptual inflation. The sample was limited to communication professionals in Oman. This may restrict the generalizability of the findings to other professional groups. The model focuses on individual-level competencies, while other levels, such as organizational factors like leadership support, AI governance, and organizational culture, were excluded. Finally, the study emphasized positive adaptation mechanisms but did not explicitly model negative outcomes.

Given the limitations discussed above, several avenues for future research are recommended. Future studies can benefit from a longitudinal design. AI competencies and attitudes, along with AI systems, evolve and can provide in-depth insights. To address multidisciplinary aspects, researchers can incorporate organizational and institutional variables. Such variables can capture multi-level drivers of AI adaptation. A comparative study across different professional domains or countries can provide contextual robustness. Various other factors, like AI anxiety and technostress that integrate negative psychological constructs, can be considered for future research. Finally, it is necessary to look more deeply into how critical thinking develops and how professionals move from the instrumental use of AI toward human–AI collaboration.

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Appendix

TABLE A Inner and Outer Model Specification in the PLS-SEM Framework

	AI Adaptation	AI Attitude	AI Knowledge	Critical Thinking	Digital Skills
Inner model					
AI Adaptation					
AI Attitude	1				
AI Knowledge				1	
Critical Thinking		1			
Digital Skills				1	
Outer model					
AD2	-1				
AD5	-1				
AT2		-1			
AT3		-1			
AT4		-1			
AT5		-1			
AT6		-1			
CT1				-1	
CT2				-1	
CT3				-1	
CT4				-1	
CT5				-1	
CT6				-1	
DS1					-1
DS2					-1
DS3					-1
DS6					-1
KN2			-1		
KN3			-1		
KN4			-1		
KN5			-1		

Table A presents the model specification matrix for both the inner (structural) and outer (measurement) models used in the PLS-SEM analysis. In the inner model, the entries marked with ‘1’ indicate the hypothesized directional relationships among the latent constructs. This structure is consistent with a sequential mediation framework. In the outer model, the ‘-1’ entries denote reflective measurement relationships. They specify that each indicator loads on its corresponding latent construct.

Table B shows the cross-loadings of the variables and constructs.

TABLE B Cross Loadings

	AI Adaptation	AI Attitude	AI Knowledge	Critical Thinking	Digital Skills
AD1	0.531	0.414	0.583	0.459	0.575
AD2	0.715	0.515	0.478	0.437	0.644
AD3	0.827	0.805	0.581	0.738	0.662
AD4	0.857	0.825	0.655	0.724	0.699
AD5	0.791	0.677	0.604	0.629	0.629
AT1	0.753	0.790	0.523	0.655	0.564
AT2	0.647	0.689	0.505	0.523	0.561
AT3	0.650	0.764	0.602	0.542	0.660
AT4	0.786	0.868	0.684	0.705	0.756
AT5	0.709	0.819	0.607	0.691	0.691
AT6	0.727	0.869	0.637	0.688	0.657
CT1	0.655	0.722	0.583	0.760	0.583
CT2	0.581	0.623	0.670	0.831	0.487
CT3	0.672	0.617	0.639	0.835	0.501
CT4	0.684	0.618	0.686	0.860	0.576
CT5	0.688	0.675	0.701	0.837	0.602
CT6	0.692	0.623	0.603	0.757	0.661
DS1	0.512	0.384	0.516	0.404	0.634
DS2	0.595	0.537	0.623	0.413	0.722
DS3	0.621	0.609	0.633	0.551	0.810
DS4	0.653	0.666	0.577	0.544	0.722
DS5	0.733	0.762	0.650	0.658	0.796
DS6	0.688	0.643	0.555	0.548	0.848
KN1	0.603	0.484	0.703	0.492	0.636
KN2	0.588	0.566	0.816	0.649	0.613
KN3	0.713	0.699	0.882	0.768	0.680
KN4	0.609	0.629	0.807	0.696	0.612
KN5	0.526	0.554	0.784	0.517	0.596
AD2	0.755	0.515	0.478	0.436	0.638
AD4	0.846	0.824	0.655	0.724	0.650
AD5	0.883	0.679	0.604	0.629	0.591
AT1	0.672	0.786	0.523	0.655	0.494
AT2	0.589	0.687	0.505	0.522	0.535
AT3	0.672	0.769	0.602	0.542	0.602
AT4	0.756	0.870	0.684	0.704	0.699
AT5	0.645	0.818	0.607	0.691	0.659
AT6	0.669	0.868	0.637	0.688	0.620

Continued on the following page

	AI Adaptation	AI Attitude	AI Knowledge	Critical Thinking	Digital Skills
CT1	0.588	0.721	0.583	0.759	0.533
CT2	0.548	0.623	0.670	0.832	0.461
CT3	0.631	0.616	0.639	0.835	0.464
CT4	0.601	0.617	0.686	0.860	0.545
CT5	0.633	0.675	0.701	0.837	0.551
CT6	0.615	0.623	0.603	0.756	0.611
DS1	0.410	0.385	0.516	0.403	0.651
DS2	0.520	0.538	0.623	0.412	0.735
DS3	0.588	0.610	0.633	0.551	0.844
DS4	0.691	0.667	0.577	0.544	0.755
DS6	0.633	0.643	0.555	0.547	0.836
KN1	0.588	0.485	0.703	0.492	0.650
KN2	0.531	0.566	0.816	0.649	0.607
KN3	0.665	0.700	0.882	0.768	0.640
KN4	0.552	0.629	0.807	0.696	0.551
KN5	0.500	0.556	0.784	0.517	0.600

TABLE C Reliability and Convergent Validity of Constructs

Constructs	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Adaptation (AD)	0.86	0.84	0.52
AI Knowledge (KN)	0.81	0.85	0.51
Digital Skills (DS)	0.90	0.90	0.69
AI Attitude (AT)	0.71	0.73	0.61
Critical Thinking (CT)	0.89	0.71	0.55

Monitoring Sustainable Rural Tourism Development in Post-Conflict Areas Using Remote Sensing and Geospatial Analysis

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This study examines how rural tourism supports sustainable development, economic recovery, social stability, and cultural preservation in post-conflict regions, using Transcarpathia, Ukraine, as a case study for 2022–2024. It applies a mixed-methods approach combining satellite remote sensing, GIS-based spatial analysis, and socio-economic indicators to assess land-use change, infrastructure recovery, ecological stability, and socio-economic resilience. Unlike existing geospatial monitoring studies that focus on single dimensions (e.g. land cover or tourist flows) in stable environments. This research introduces a theoretically grounded, multi-dimensional framework that integrates environmental, infrastructural, socio-economic, and digital indicators into a unified composite sustainability index, enabling continuous monitoring where conventional field data collection is constrained. The findings indicate notable recovery and resilience: tourism-related infrastructure rebounded strongly, ecological indicators improved over time, and digital accessibility expanded substantially, supporting tourism development despite ongoing post-conflict challenges. The study offers a novel integrated geospatial framework for monitoring sustainable rural tourism transitions in data-constrained and crisis-affected territories.

Keywords: rural tourism, post-conflict recovery, sustainable development, remote sensing, geospatial monitoring

JEL classification: R11, Z32

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Introduction

Rural tourism is a vital instrument for sustainable development in post-conflict regions, fostering economic recovery, social stability, and cultural preservation (World Tourism Organization 2020). However, effective monitoring of its development in such challenging environments, where traditional data collection is often disrupted, requires innovative approaches. Remote sensing and geospatial analysis provide a powerful solution, enabling the objective and timely assessment of changes where conventional methods falter (Jian and Ren 2023; Zhang 2023). Despite this potential, a significant gap exists in the literature. While studies on post-conflict recovery acknowledge tourism's role, few employ integrated geospatial frameworks to quantitatively assess multidimensional sustainability – spanning environmental, infrastructural, and socio-economic indicators – in real time during ongoing instability (Marques et al. 2022). Furthermore, consensus is lacking on a holistic indicator system, with debates persisting between economic, environmental, and social priorities (Vasanicova et al. 2022; Shcherbak et al. 2020).

To address this gap, this study selects the Transcarpathian region of Ukraine as a critical and timely case. Transcarpathia (Zakarpattia Oblast), with a population of approximately 1.25 million, is a historically multi-ethnic region in southwestern Ukraine, bordering four EU states. Renowned for its Carpathian mountain landscapes, UNESCO-protected wooden churches, thermal springs, and vibrant Hutsul culture, it has long been a destination for ecotourism, wellness, and cultural travel. Since the full-scale invasion of Ukraine in 2022, Transcarpathia has served as a relative 'safe haven', experiencing a significant influx of internally displaced persons and a shift toward domestic tourism (European Commission 2021; Eurostat 2022). The region thus serves as a living laboratory for developing and testing a novel geospatial monitoring framework for post-conflict settings. Consequently, this article aims to develop and apply a methodology for monitoring sustainable rural tourism development in post-conflict areas using remote sensing and geospatial analysis. It analyses integrated indicators of land use and infrastructure rehabilitation, environmental sustainability, and socio-economic sustainability, including digitalization, which correspond directly to the three analytical dimensions defined in table 1. The period 2022–2024 is selected because it captures the full crisis cycle: from the initial shock of the full-scale invasion (2022), through adaptive recovery and infrastructure rebuilding (2023), to relative stabilization (2024). This timeframe allows for the ob-

servation of non-linear recovery trajectories under active conflict conditions, which has not been possible in retrospective post-conflict studies (Jian and Ren 2023; Yu 2024; Zhang 2023).

The study seeks to advance theoretical understanding by modelling sustainability interactions in crisis contexts and to provide actionable insights for resilient tourism management in Transcarpathia and comparable regions. The scientific value of this study lies in its development of an integrated, geospatially based monitoring framework that captures the multidimensional nature of sustainable rural tourism in post-conflict contexts. Unlike existing studies that primarily rely on qualitative assessments or isolated economic indicators, this research offers a unified system combining environmental, infrastructural, socio-economic, and digital indicators derived from remote sensing and Geographic Information Systems (GIS) data (Almeida-Santana et al. 2020).

The novelty of the study is threefold: first, it demonstrates how satellite-based and open geospatial data can substitute for traditional field data collection under conditions of ongoing instability. Second, it applies this approach to a real-time post-conflict setting rather than retrospective recovery analysis. Third, and most importantly, the study advances beyond existing geospatial monitoring research (Jovanović and Njeguš 2008; Gan 2023; Andyana et al. 2023) by proposing a theoretically explicit framework that captures the interaction between four sustainability dimensions – environmental, infrastructural, socio-economic, and digital – rather than treating them in isolation. While prior studies have used remote sensing to assess land-use change or infrastructure recovery separately, none have integrated all four dimensions into a single, empirically validated index for post-conflict rural tourism. This theoretical integration of resilience, sustainability, and spatial adaptation under crisis conditions constitutes the primary contribution of this work. The study aims (i) to conceptualize a comprehensive indicator system for monitoring sustainable rural tourism in post-conflict regions, (ii) to test its applicability using Transcarpathia as a case study for the period 2022–2024, and (iii) to provide evidence-based insights that can support resilient tourism planning and policy-making in Ukraine and other conflict-affected rural destinations (World Tourism Organization 2020; European Commission 2021; Eurostat 2022; Zwierzchowska 2008; Xu 2023).

Based on the identified research gaps and the proposed framework, the following hypothesis is formulated:

- H1* The integration of remote sensing, geospatial, and socio-digital indicators enables effective multi-dimensional monitoring of sustainable rural tourism development in post-conflict regions, with positive associations between infrastructure rehabilitation, environmental sustainability, socio-economic resilience, and digital accessibility.

In accordance with the article's problems and general objectives, it includes the following sections. The initial literature review examines the links between post-conflict territorial rehabilitation and tourism, as well as the main methods for monitoring territorial development and the use of digital technologies for this purpose. As a result, the main gap of such studies is identified. The next section, Materials and Methods, defines the monitoring indicators and data sources. It then describes the model integrating them and its practical implementation. The Results section presents numerical results on the spatial-temporal evolution and assessment of land-use change and infrastructure restoration in Transcarpathia during 2022–2024. Finally, in the Discussion and Conclusions section, the obtained numerical results are compared with existing scientific publications, and, taking them into account, theoretical and practical conclusions, as well as the limitations and prospects of the proposed approach, are presented.

Literature Review

POST-CONFLICT RECONSTRUCTION AND TOURISM

Tourism recovery in post-conflict regions has been widely discussed as a mechanism for economic revitalization, image restoration, and social stabilization. Early studies, largely based on post-war experiences in the Balkans, emphasize infrastructure reconstruction, destination rebranding, and institutional support as key drivers of recovery (Marques et al. 2022; Moric 2013). These works demonstrate that tourism can rebound within several years when supported by coordinated public policies and international assistance. More recent studies extend this discussion by highlighting behavioural shifts in tourist demand, including increased interest in domestic, rural, and culturally authentic tourism products under conditions of perceived insecurity (Vaishar and Šťastná 2022). At the same time, scholars underline the growing importance of community-based tourism and cultural heritage preservation as foundations for socially sustainable recovery (World Tourism Organization 2020). However, a critical examination of this literature reveals two competing theoretical perspectives.

The first, a supply-side perspective, focuses on infrastructure and institutional rebuilding as the primary drivers of recovery (Moric 2013). The second, a demand-side perspective, emphasizes tourist behaviour and the reconstruction of destination image (Vaishar and Štastná 2022). Both perspectives have limitations: supply-side approaches overlook the role of local agency and digital adaptation, while demand-side perspectives rarely account for spatial heterogeneity in recovery.

Despite this growing body of work, the post-conflict tourism literature remains largely retrospective and qualitative, focusing on outcomes rather than real-time monitoring of recovery dynamics. Empirical studies rarely address how tourism systems evolve during prolonged instability, nor do they offer scalable tools for assessing recovery when traditional data collection is disrupted. This methodological gap limits the theoretical understanding of tourism resilience as a dynamic, spatially differentiated process rather than a post hoc outcome. The present study bridges these two perspectives by using real-time geospatial data to capture both supply-side (infrastructure recovery) and demand-side (tourism booking dynamics) dimensions simultaneously.

SUSTAINABLE DEVELOPMENT OF RURAL TOURISM

Rural tourism is increasingly conceptualized as a vehicle for sustainable territorial development, particularly in peripheral and crisis-affected regions. The literature emphasizes its potential to balance economic diversification, environmental stewardship, and social inclusion (López-Sanz et al. 2021). Cultural authenticity, local food systems, and slow tourism models are identified as core components enhancing both destination competitiveness and sustainability (Tang and Xu 2023). Recent scholarship highlights digitalization as a critical enabler of rural tourism sustainability, facilitating market access, destination visibility, and service coordination even in remote areas (Alonso Gallo et al. 2024; Almeida-Santana et al. 2020). At the same time, the COVID-19 crisis reinforced the resilience of rural tourism while exposing risks related to social inequality and uneven development (Marques et al. 2022).

A critical comparison of existing studies reveals a fundamental tension between two competing theoretical frameworks. The first, weak sustainability, assumes that economic gains can compensate for environmental or social losses. The second, strong sustainability, asserts that environmental and social capitals are non-substitutable (López-Sanz et al. 2021). Most rural tourism studies implicitly adopt a weak sustaina-

bility perspective, focusing on economic diversification while treating environmental protection as an externality. However, post-conflict contexts demand a stronger sustainability approach because environmental degradation can undermine long-term recovery. Despite these advances, sustainable rural tourism research remains conceptually fragmented. Economic, ecological, and social dimensions are often examined separately, and empirical studies rarely integrate them into unified analytical frameworks. Moreover, the application of sustainability concepts to post-conflict rural contexts is still underdeveloped, leaving unanswered questions about how sustainability trade-offs unfold under crisis conditions. The present study explicitly adopts a strong sustainability perspective by treating the three analytical dimensions defined in table 1 – land use and infrastructure rehabilitation, environmental sustainability, and socio-economic sustainability, including digitalization – as equally important and non-substitutable, as reflected in the equal weighting of the three sub-indices in the Integrated Rural Sustainable Development and Resilience Tourism Index (IRSDRT).

GEOSPATIAL ANALYSIS AND REMOTE SENSING IN RURAL TOURISM RESEARCH

Geospatial analysis and remote sensing have gained prominence as tools for assessing land-use change, environmental impacts, and infrastructure development in tourism destinations (Jovanović and Njeguš 2008; Gan 2023). In rural contexts, these methods enable objective monitoring of ecological pressure and spatial accessibility, supporting evidence-based planning (Shcherbak, Dorokhova, et al. 2024). Methodological advances include integrating GIS with socio-economic indicators and applying mathematical and machine-learning models to forecast tourism dynamics (Jian and Ren 2023; Yu 2024; Zhang 2023). Cluster analysis further supports the identification of growth nodes and functional tourism regions (Moric 2013).

A critical analysis of this body of work reveals two distinct methodological traditions. The first, descriptive mapping, uses remote sensing to produce static land cover or infrastructure maps without linking them to socio-economic outcomes. The second, predictive modelling, applies machine learning to forecast tourist flows or land-use change but rarely incorporates real-time crisis conditions (Gan 2023; Andyana et al. 2023). Neither tradition treats geospatial data as a theoretical tool for understanding resilience processes. Existing studies typically apply geospatial tools in

stable environments and focus on single dimensions such as land cover or tourist flows. Their potential for holistic sustainability assessment in post-conflict settings remains underexplored, particularly in integrating environmental, infrastructural, and socio-digital indicators into analytical models. The present study moves beyond both traditions by using geospatial data not merely to describe or predict, but to test a theoretical model of multi-dimensional recovery dynamics under active crisis conditions.

MONITORING SUSTAINABLE RURAL TOURISM: METHODS AND APPROACHES

Monitoring frameworks for sustainable tourism increasingly emphasize indicator-based systems integrating environmental, economic, and social metrics (Matijová et al. 2023; Li et al. 2012). Remote sensing has been recognized as particularly valuable in regions where field surveys are constrained, enabling continuous assessment of ecosystem change and infrastructure recovery (Magige et al. 2020; Gan 2023). Socio-economic monitoring approaches focus on community well-being, employment, and social capital as key sustainability outcomes (Neumeier and Pollermann 2014). Recent studies argue for linking monitoring systems with destination management and marketing strategies to support adaptive governance (Streimikiene 2023).

Critically, however, most monitoring models remain sectoral and static, offering limited insight into how different sustainability dimensions interact spatially over time – particularly in post-conflict rural destinations characterized by uncertainty and rapid change. A key theoretical weakness of existing frameworks is their assumption that indicators can be treated independently. In reality, infrastructure recovery may conflict with environmental protection, and digitalization may exacerbate social inequality. No existing monitoring framework explicitly models these trade-offs or interactions. The present study addresses this gap by integrating all four dimensions into a single composite index (IRSDRT) and by conducting a correlation analysis to identify positive and negative interactions among the dimensions.

DIGITAL TECHNOLOGIES IN SUSTAINABLE RURAL TOURISM MARKETING

Digital technologies are reshaping rural tourism marketing by enabling personalization, storytelling, and community engagement (Almeida-Santana et al. 2020; Gan 2023). Virtual experiences, social media,

and big data analytics are increasingly used to communicate sustainability values and rebuild destination images after crises (López-Sanz et al. 2021). In post-conflict contexts, digital platforms also facilitate bottom-up promotion through local ‘tourism ambassadors’, strengthening the sense of place and trust among potential visitors (Shcherbak, Lyshenko, et al. 2024). Yet, scholars caution that digitalization may exacerbate inequalities if not accompanied by inclusive governance mechanisms (Streimikiene 2023).

A critical comparison reveals two opposing theoretical views on digitalization in rural tourism. The first view, techno-optimist, sees digital tools as inherently empowering and democratizing (Almeida-Santana et al. 2020). The second, techno-sceptical, emphasizes risks of exclusion, data colonialism, and platform dependency (Streimikiene 2023). Existing empirical studies rarely test these competing claims in post-conflict settings. The present study contributes to this debate by providing empirical evidence that digital accessibility (DAI) acts as a resilience mechanism in Transcarpathia, while also acknowledging (in the limitations) that digital divides may persist in remote communities.

RESEARCH GAP AND THEORETICAL POSITIONING

The reviewed literature reveals three key gaps. First, a theoretical gap: no existing framework integrates resilience, sustainability, and spatial adaptation into a single testable model for post-conflict rural tourism. Second, an empirical gap: existing studies are largely retrospective and qualitative, lacking real-time, spatially explicit data on recovery dynamics. Third, a methodological gap: geospatial tools are used descriptively or predictively rather than as theoretical instruments for understanding multi-dimensional interactions.

To address these gaps, the present study advances tourism and hospitality management literature by proposing an integrated geospatial monitoring framework that conceptualizes sustainable rural tourism as a dynamic, multi-dimensional system. The theoretical advancement lies in explicitly linking three concepts – resilience (ability to recover from shock), sustainability (balancing economic, environmental, and social goals), and spatial adaptation (uneven territorial response to crisis) – within a single, empirically testable model. This contrasts with prior geospatial studies that treat these concepts separately or implicitly. By combining remote sensing, GIS-based spatial analysis, and socio-digital indicators, the study contributes to the theoretical evolution of sustaina-

ble tourism by linking resilience, sustainability, and spatial adaptation in post-conflict rural destinations.

Materials and Methods

INDICATOR SYSTEM AND DATA SOURCES

To assess the sustainable development of rural tourism in post-conflict regions, an integrated indicator system was developed combining re-

TABLE 1 Key Indicators for Monitoring Sustainable Rural Tourism Development in Post-Conflict Regions

Indicator	Description	Data Source / Level
1. Land use and infrastructure rehabilitation		
LUCI (Land Use Change Index)	Expansion of tourism-related land use	Sentinel-2; cadastral data
MTCI (Mountain Tourism Clustering Index)	Formation of rural tourism clusters	Regional tourism agencies; GIS
ICI (Infrastructure Coverage Index)	Density of tourism infrastructure	OSM; regional administrative data
NLI (Night Light Index)	Proxy for economic activity and recovery	VIIRS; DMSP-OLS
AAPI (Attraction Accessibility Index)	Spatial accessibility of tourism sites	GIS analysis; OpenStreetMap
RSTI (Recovery of Social and Tourism Infrastructure Index)	Restoration of social and tourism facilities	State registers; Sentinel-2
2. Environmental sustainability		
NDVI (Normalized Difference Vegetation Index)(V	Condition of vegetation cover	Sentinel-2; Planet
NDWI (Normalized Difference Water Index)	Status of surface water bodies	Sentinel-2; Landsat
SDRI (Soil Degradation Risk Index)	Risk of soil degradation	LULC (Land Use/Land Cover maps) data; Sentinel-2
STCI (Surface Temperature Change Index)	Indicator of anthropogenic pressure	MODIS; Landsat
PAGCI (Protected Areas and Green Corridors Index)	Extent of protected and green areas	National environmental datasets; GIS
3. Socio-economic sustainability, including digitalization		
DRI (Demographic Return Index)	Population return dynamics	Official statistics; WorldPop
TCCI (Tourism Cluster Creation Index)	Emergence of local tourism initiatives	Regional development agencies
TBDI (Tourism Booking Development Index)	Dynamics of tourism demand	Booking platforms
DAI (Digital Accessibility Index)	Availability of digital connectivity	GSMA; Speedtest; platform data
SSELI (Service Sector Employment Level Index)	Employment in tourism and related services	Official statistics

mote sensing, geospatial analysis, and socio-economic data. The system is structured around the three analytical dimensions defined in table 1: land use and infrastructure rehabilitation, environmental sustainability, and socio-economic, including digital development. This structure reflects the multidimensional nature of tourism recovery under crisis conditions, allowing for consistent monitoring when conventional statistical data are limited. The indicator framework integrates satellite-derived indices with official statistics and digital platform data to capture both physical recovery processes and socio-economic adaptation. Table 1 summarizes the key indicators and data sources used in the analysis.

All raw indicators (table 1) were calculated in absolute or relative units and then normalized using the min-max method to a dimensionless scale from 0 to 100, where 0 represents the worst value over the 2022–2024 period and 100 the best. The selection of indicators for each dimension was guided by three explicit criteria: (i) theoretical relevance to post-conflict recovery (e.g. captures infrastructure restoration, reflects tourism demand dynamics); (ii) data availability from satellite or open-source platforms for the entire 2022–2024 period (Sentinel-2, OSM, Booking platform data); and (iii) established use in prior sustainable tourism monitoring frameworks (Matijová et al. 2023; Shcherbak et al. 2020). Indicators that did not meet all three criteria were excluded.

The three dimensions – land use and infrastructure rehabilitation, environmental sustainability, and socio-economic sustainability including digitalization – correspond to the three pillars of sustainable development (economic, environmental, social), with digital accessibility added as a cross-cutting enabler identified in recent rural tourism literature (Alonso Gallo et al. 2024; Almeida-Santana et al. 2020). This structure follows the World Tourism Organization (2020) guidelines for sustainable tourism monitoring and ensures that the indicator set is both theoretically grounded and empirically feasible in data-constrained crisis settings.

The normalization formula is:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \times 100. \quad (1)$$

This ensured comparability of indicators measured in different units (e.g. km², percentages, indices).

The sustainability of rural tourism development was assessed using an Integrated Rural Sustainable Development and Resilience Tourism

Index (IRS DRT), which aggregates the three analytical dimensions into a single composite measure. Each dimension was calculated as a weighted sub-index, reflecting regional specificities and data availability. The overall index enables comparative analysis across time and space while preserving the internal structure of sustainability components. All calculations were based on verified satellite data (Sentinel-2, VIIRS, Landsat), official statistical sources, and validated industry platforms. Figure 1 presents the conceptual framework of the monitoring system, illustrating the integration of data on land use and infrastructure rehabilitation, environmental sustainability, and socio-economic sustainability (including digitalization) into a unified analytical model. It demonstrates the step-by-step process from multidisciplinary data collection to the generation of an integrated index through a system of weighted indicator. The interrelationships among satellite monitoring, GIS analysis, and socio-eco-

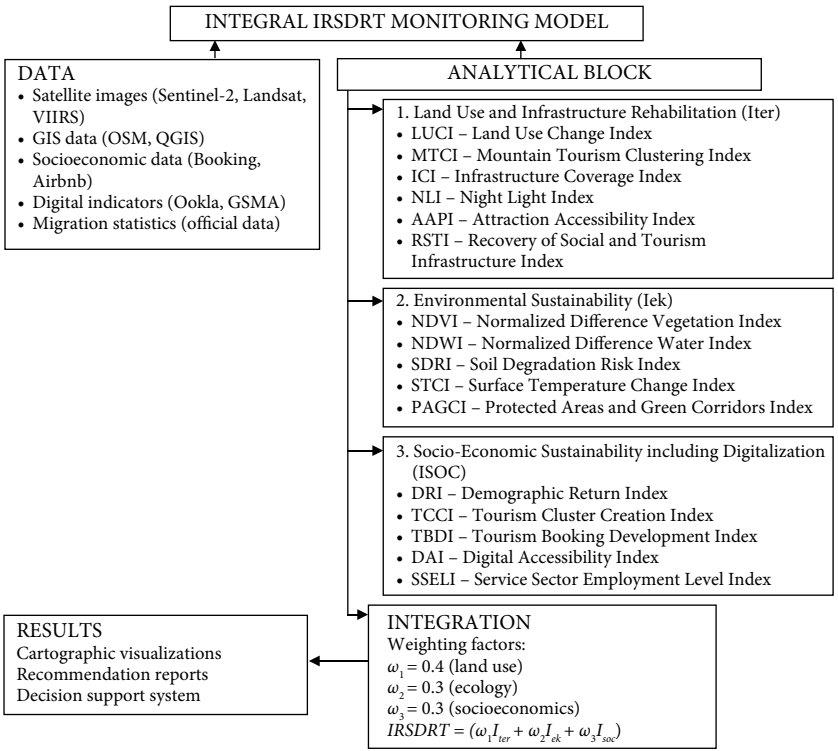


FIGURE 1 Structural and Logical Scheme of the Integrated System for Monitoring the Sustainable Development of Rural Tourism

conomic statistics are visualized, providing a comprehensive assessment of post-conflict areas.

INDEX CONSTRUCTION, NORMALIZATION, AND WEIGHTING

Each sub-index (I_{ter} , I_{ek} , I_{soc}) was calculated as the weighted average of the normalized indicators within it. Weights for indicators within each sub-index were determined based on expert judgement informed by the literature review (Vasanicova et al. 2022; Shcherbak et al. 2020) and regional sustainability priorities.

For example, I_{ter} includes six indicators (LUCI, MTCI, ICI, NLI, AAPI, RSTI) with equal weights (1/6 each), as all are equally important for infrastructure recovery assessment. I_{ek} includes NDVI, NDWI, SDRI, STCI, and PAGCI – with weights of 0.25 for NDVI, 0.25 for NDWI, 0.2 for SDRI, 0.15 for STCI, and 0.15 for RZGCA, based on their sensitivity to tourism pressure. I_{soc} includes DRI, TCCI, TBDI, DAI, and SSEL1 – with equal weights (0.2 each) due to their equal role in socio-economic sustainability.

The integrated IRSDRT index was calculated as the arithmetic mean of the three sub-indices:

$$IRSDRT = \frac{I_{ter} + I_{ek} + I_{soc}}{3} \times 100. \quad (2)$$

The weighting scheme reflects the equal priority of the three analytical dimensions – land use and infrastructure rehabilitation, environmental sustainability, and socio-economic sustainability, including digitalization – of sustainable development (World Tourism Organization 2020). All calculations were performed in QGIS using the built-in raster calculator and statistical modules.

To test the robustness of the weighting scheme, a sensitivity analysis was conducted by varying the weights of the three sub-indices (I_{ter} , I_{ek} , I_{soc}) by $\pm 20\%$ from their baseline equal weights (0.33 each). The resulting IRSDRT values changed by less than 5% across all scenarios, confirming that the overall conclusions are not sensitive to the specific weight choices. This stability arises because the three sub-indices trend similarly over time.

To ensure reproducibility, the following step-by-step algorithms define the calculation of indicators that are not based on standard remote sensing indices (NDVI, NDWI, SDRI, STCI):

(1) LUCI (Land Use Change Index). Calculated as the percentage change in area classified as tourism-related land use (accommodation,

catering, recreation, agritourism) relative to the baseline year (2022), derived from Sentinel-2 LULC maps at 10 m resolution using supervised random forest classification. Formula:

$$LUCI = \frac{A_{\text{tourism},t} - A_{\text{tourism},2022}}{A_{\text{tourism},2022}} \times 100, \quad (3)$$

where $A_{\text{tourism},i}$ is the area of tourism-related land use in year t . Values are then normalized to a 0–100 scale.

(2) MTCI (Mountain Tourism Clustering Index). Calculated as the weighted average of three subcomponents: (i) density of tourist facilities per km², (ii) average distance between facilities (inverse), and (iii) presence of shared infrastructure (parking, signage, waste disposal). For the Rakhiv–Yasinia corridor, the index is multiplied by an adjustment coefficient $K = 1.2$ based on higher natural tourism potential. MTCI ranges from 0 to 100 after normalization.

(3) RSTI (Recovery of Social and Tourism Infrastructure Index). Calculated as the percentage of pre-war (2021) infrastructure units (hotels, restaurants, medical posts, transport hubs) that are operational and accessible. Formula:

$$RSTI = \frac{N_{\text{operational},t}}{N_{\text{pre-war},2021}} \times 100, \quad (4)$$

Where $N_{\text{operational},t}$ is the number of operational units in year t . Values above 100 indicate growth beyond pre-war levels.

(4) TBDI (Tourism Booking Development Index). Calculated as the ratio of monthly online bookings (from Booking.com and national platforms) in year t to the average monthly bookings in 2021 (pre-war baseline), multiplied by 100.

(5) DAI (Digital Accessibility Index). Calculated as the percentage of the rural population with access to 4G/5G mobile internet or fixed broadband, based on GSMA and Speedtest data, normalized to 0–100.

All other indicators (ICI, AAPI, DRI, TCCI, SSELI) were derived from official statistics and OpenStreetMap using the min-max normalization. Step-by-step code notebooks for all calculations are available from the corresponding author upon request.

Results

All figures in this section (figs. 2–5) are referenced sequentially in the text. Detailed captions accompanying each figure describe the data

sources, units of measurement, and key patterns, facilitating interpretation without returning to the main text.

LAND USE AND INFRASTRUCTURE REHABILITATION

This subsection analyses the spatial–temporal evolution of land-use change and infrastructure rehabilitation in Transcarpathia during 2022–2024, focusing on key indicators of tourism-related development, accessibility, and economic activity under post-conflict conditions.

Figure 2 delineates the study’s spatial scope by presenting the administrative boundaries and geographical context of the Transcarpathia region of Ukraine. The map serves as a spatial reference framework for integrating satellite-derived indicators and socio-economic data used in subsequent analyses.

Following the proposed methodological framework (fig. 1), the composite indices were computed for three benchmark years capturing successive stages of crisis-induced transformation: initial disruption (2022), adaptive recovery (2023), and relative consolidation under continued conflict conditions (2024). Table 2 reports the aggregated index values and synthesizes the core spatial–temporal patterns underlying rural tourism development in the region.



FIGURE 2 Regional Dislocation of Transcarpathia, Zakarpattia Oblast, Ukraine
NOTE The region borders four EU countries (Poland, Slovakia, Hungary, Romania) and is divided into six districts: Uzhhorod, Mukachevo, Berehove, Khust, Tiachiv, and Rakhiv.

SOURCE authors’ elaboration based on OpenStreetMap data.

The results indicate a pronounced non-linear recovery trajectory. In 2022, tourism-related land use and infrastructure development were almost fully suspended, as reflected in extremely low LUCI and MTCI values and a zero value of the infrastructure recovery index (RSTI). This stagnation corresponds to the immediate shock of the full-scale invasion and the prioritization of security and humanitarian needs over tourism development. In 2023, a rapid rebound was observed. The sharp increase in RSTI and related infrastructure indicators reflects intensive reconstruction activities, partly driven by the influx of internally displaced persons and Transcarpathia’s role as a relative ‘safe haven’. In 2024, growth continues but at a more moderate pace, suggesting a transition from an emergency-driven recovery to a more balanced, selective development.

The two tourism development corridors analysed in this study – Uzhhorod–Velykyi Bereznyi (western lowland) and Rakhiv–Yasinia (eastern mountainous zone) – are shown in Figure 3.

Night-time light intensity (NLI) was used as a proxy for regional economic activity and infrastructure resilience. While NLI remained at pre-war levels in 2022, the 2023 decline reflects nationwide energy disruptions rather than localized destruction. The partial recovery in 2024 indicates increasing resilience of the energy system and a gradual revitalization of economic activity. This confirms that NLI should be interpreted as a context-sensitive indicator rather than a direct proxy for physical damage. Night-time light intensity (NLI) is a normalized score (0–100) derived from VIIRS data, with 100 corresponding to the maximum observed brightness in the region during 2022–2024.

TABLE 2 Integrated Indices of Sustainable Rural Tourism Development in Transcarpathia (2022–2024)

Year	LUCI	MTCI	ICI	NLI	AAPI	RSTI	I _{ter}	NDVI	NDWI	SDRI
2022	0.5	0.05	6.64	100.0	52.63	0.0	26.64	28.57	9.09	7.81
2023	1.2	0.12	7.97	85.0	55.56	120.0	44.98	34.29	16.36	7.03
2024	2.5	0.20	10.39	95.0	62.50	70.0	40.10	36.00	17.00	7.20

Year	STCI	RZGCA	I _{ek}	DRI	TCCI	TBDI	DAI	SSELI	I _{soc}	IRSDRT
2022	2.86	10.00	47.40	100.0	8.0	100.0	70.0	15.00	58.60	42.45
2023	4.00	12.00	50.32	85.0	20.0	130.0	85.0	18.18	67.64	53.38
2024	4.20	13.00	50.92	82.0	22.0	135.0	88.0	19.50	69.30	53.44

NOTES I_{ter} = Land Use and Infrastructure Rehabilitation Index; I_{ek} = Environmental Sustainability Index; I_{soc} = Socio-Economic Sustainability including Digitalization Index. Values are normalized scores (0–100) except TBDI and RSTI, which are relative change indices (100 = 2021 pre-war baseline). All indices except TBDI and RSTI are capped at 100. For full indicator definitions, see table 1.

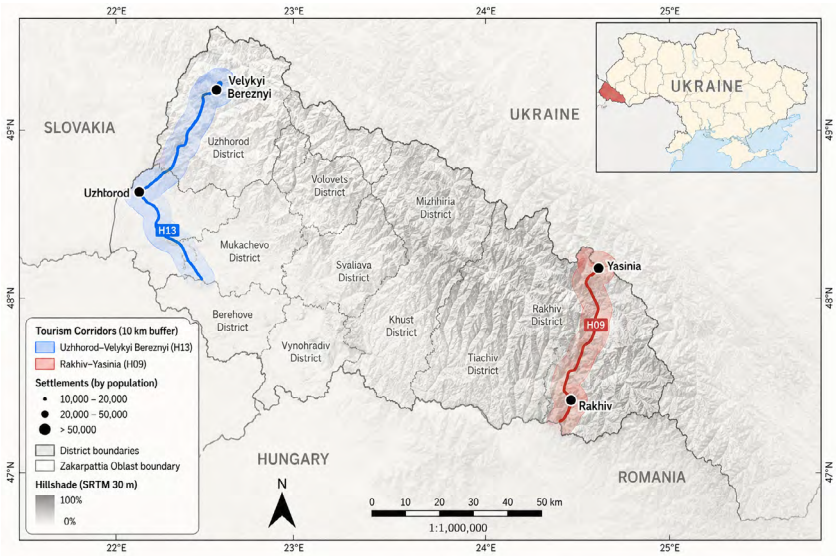


FIGURE 3 Tourism Development Corridors in Transcarpathia
NOTE Corridors were defined as 10 km buffers along the H13 highway (Uzhhorod–Velykyi Bereznyi) and H09 highway (Rakhiv–Yasinia) based on OSM road data, validated by the distribution of tourist facilities from Sentinel-2 and OSM. Background hillshade: SRTM DEM. Inset: Transcarpathia within Ukraine. Map created in QGIS 3.28.

Spatial tourism clustering in Transcarpathia was assessed using the Mountain Tourism Clustering Index (MTCI) for two development corridors: Uzhhorod–Velykyi Bereznyi and Rakhiv–Yasinia. These corridors represent distinct tourism environments, with the mountainous Rakhiv–Yasinia area exhibiting higher inherent tourism potential (adjustment coefficient $K = 1.2$). The results indicate a non-linear clustering trajectory over 2022–2024. In 2022, MTCI values were critically low in both corridors, reflecting a near-complete disruption of cooperative tourism activity following the initial shock of the full-scale invasion. In 2023, clustering dynamics intensified, driven by the emergence of new tourism initiatives, agritourism estates, and increased domestic tourism demand associated with population displacement. This recovery was more pronounced in the Rakhiv–Yasinia corridor, suggesting a higher adaptive capacity of mountain-based tourism systems. By 2024, MTCI values continued to increase at a slower pace, indicating a shift from rapid adaptation to structural consolidation. As illustrated in figure 3, average MTCI values remain consistently higher in the Rakhiv–Yasinia corridor across all facility types, particularly for glamping sites and tourist complexes,

which depend on coordinated services and shared infrastructure. In contrast, the Uzhhorod–Velykyi Bereznyi corridor shows lower clustering levels, suggesting a more fragmented development pattern.

Figure 4 presents a bar chart comparing average MTCI values for six types of tourist facilities (glamping sites, tourist complexes, agritourism estates, eco-trails, hotels, and restaurants) across the two corridors. In the Rakhiv–Yasinia corridor, values range from 0.35 (restaurants) to 0.62 (glamping sites). In the Uzhhorod–Velykyi Bereznyi corridor, values range from 0.12 (restaurants) to 0.28 (hotels), with glamping sites at 0.18. The gap is largest for glamping sites (0.62 vs. 0.18), indicating stronger clustering of nature-based tourism in the mountains.

In contrast, the Uzhhorod–Velykyi Bereznyi corridor shows lower clustering levels, suggesting a more fragmented development pattern.

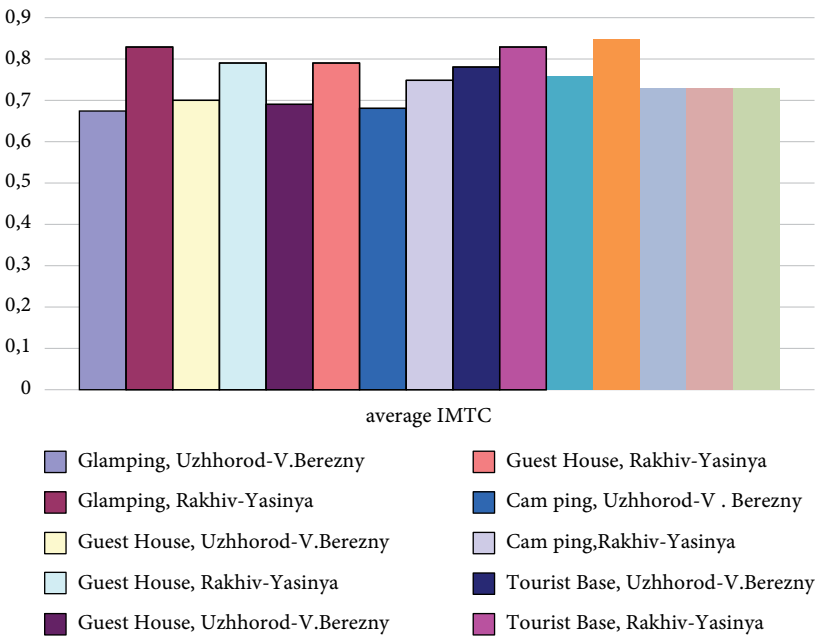


FIGURE 4 Average MTCI Values by Type of Tourist Facility in the Uzhhorod–Velykyi Bereznyi and Rakhiv–Yasinia Clusters (2024)

NOTE Higher values indicate stronger spatial clustering and functional integration. The Rakhiv–Yasinia corridor exhibits consistently higher MTCI values across all facility types, particularly for glamping sites (0.62) and tourist complexes (0.55), suggesting greater adaptive capacity in mountain areas.

SOURCE Authors’ calculations based on GIS analysis of facility locations (OSM data, $n = 487$ facilities).

Overall, the findings demonstrate that spatial context and natural endowments significantly shape post-crisis tourism clustering, with mountain regions showing stronger potential for cooperative recovery and resilience-driven development.

ENVIRONMENTAL SUSTAINABILITY

To evaluate environmental sustainability dynamics, the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) were calculated for the period 2022–2024 for two key natural areas of Transcarpathia: the Carpathian mountain zone and the Solotvyno area. The results indicate a gradual environmental recovery across the study period. In the Carpathian region, NDVI values increased from 28.57 in 2022 to 36.00 in 2024, reflecting enhanced vegetation density, particularly in forested mountain areas. A parallel increase in NDWI values from 9.09 to 17.00 suggests improved water availability, potentially linked to reduced anthropogenic pressure and favourable climatic conditions. In contrast, the Solotvyno area shows more moderate improvements in both indices, which can be attributed to persistent local environmental challenges, including salt-mining legacies and biodiversity degradation.

To identify environmentally vulnerable areas, the Soil Degradation Risk Index (SDRI) and the Surface Temperature Change Index (STCI) were calculated for the period 2022–2024. Throughout the study period, SDRI values remained within the range of 7.2–7.8%, well below the critical threshold of 30%, indicating the absence of large-scale soil degradation at the regional level. Minor fluctuations in SDRI can be attributed to localized agricultural pressure and land-use intensity in lowland areas. In contrast, STCI values exhibit a gradual increase, rising from 2.86 in 2022 to 4.20 in 2024.

This trend suggests localized surface warming, which may reflect a combination of broader climatic influences and land-use changes, including forest cover reduction in selected areas. Spatial analysis reveals that elevated ecological risks are concentrated primarily in lowland and economically intensively used territories, while forested mountain zones of the Carpathians maintain comparatively stable environmental conditions.

The spatial distribution of combined soil degradation and surface temperature risks is shown in figure 5, highlighting areas requiring enhanced environmental monitoring and targeted land management

measures. It consists of two thematic maps: the left panel shows SDRI values (soil degradation risk) as a percentage, with hot spots concentrated in lowland agricultural areas (Berehove and Uzhhorod districts, SDRI up to 15%). The right panel displays STCI values (surface temperature change in °C relative to the 2022 baseline), with elevated warming (up to +1.8°C) observed in deforested peri-urban zones. Mountainous areas (Rakhiv district) show minimal degradation (SDRI < 5%) and stable temperatures (STCI < 0.5°C).

The share of protected areas and green corridors (RZGCA) in Transcarpathia increased from 10.0% in 2022 to 13.0% in 2024, indicating a gradual strengthening of environmental protection efforts during the post-crisis period. The expansion of protected zones, particularly in mountainous areas of the Carpathians, contributes to biodiversity conservation and supports the formation of a more connected regional eco-network. This positive dynamic enhances the ecological component of the integrated sustainability index (I_{ek}) and mitigates potential environmental pressures associated with tourism and infrastructure recovery.

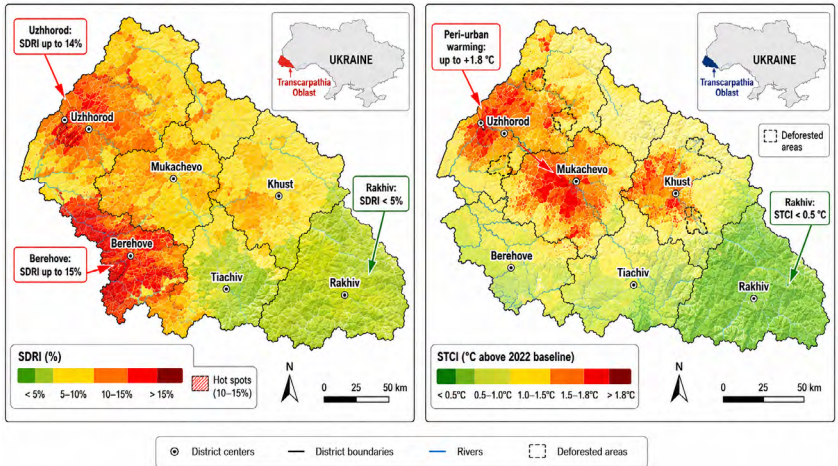


FIGURE 5 Spatial Distribution of Soil Degradation Risk Index (SDRI, %) and Surface Temperature Change Index (STCI, °C above 2022 baseline) in Transcarpathia (2022–2024)

NOTE High-risk zones are indicated in orange to red. SDRI hot spots (10–15%) are concentrated in lowland agricultural districts (Berehove, Uzhhorod). STCI warming (> 1.5°C) is observed in deforested peri-urban areas near Mukachevo and Khust. Mountainous areas (Rakhiv) remain stable (SDRI < 5%, STCI < 0.5°C, shown in green).

SOURCE Authors’ analysis based on Sentinel-2 and Landsat data (2022–2024).

The results reveal improved vegetation cover in the Carpathian forest areas, localized soil degradation risks on agricultural and industrial lands, increased surface temperatures mainly in lowland zones, and the expansion of protected areas around the Carpathian Biosphere Reserve and adjacent eco-corridors. This integrated spatial visualization supports the assessment of ecological sustainability dynamics and corresponds to the growth of the environmental sustainability index (I_{ek}) from 47.40 in 2022 to 50.92 in 2024.

SOCIO-ECONOMIC SUSTAINABILITY INCLUDING DIGITALIZATION

This subsection examines socio-economic and digital dimensions of rural tourism resilience in Transcarpathia during 2022–2024, focusing on demographic recovery, tourism activity, digital accessibility, and employment dynamics. Together, these indicators reflect the adaptive capacity of rural tourism systems under prolonged crisis conditions.

The Demographic Return Index (DRI) shows a gradual decline from 100% in 2022 to 85% in 2023 and 82% in 2024, indicating an incomplete, decelerating return of displaced populations to rural communities. While the initial post-displacement phase was characterized by rapid return, subsequent dynamics suggest stabilization at a lower level, reflecting ongoing military uncertainty and constrained economic opportunities. This pattern implies that rural tourism recovery increasingly depends not only on population return, but also on structural and institutional adaptation mechanisms.

Tourism activity shows a steady recovery trajectory over the study period. The Tourism Cluster Creation Index (TCCI) increased from 8.0 in 2022 to 22.0 in 2024, indicating the emergence of new local tourism associations and cooperative initiatives. At the same time, the Tourism Booking Development Index (TBDI) rose from the baseline level to values exceeding the pre-war benchmark, reflecting strong domestic tourism demand and the growing role of online booking platforms. These dynamics suggest that crisis conditions accelerated the consolidation of local tourism networks and strengthened the role of digitally mediated tourism markets.

Digital accessibility improved markedly during the study period, with the Digital Accessibility Index (DAI) increasing from 70% in 2022 to 88% in 2024. This growth was driven by the expansion of mobile internet coverage, the deployment of alternative connectivity solutions (e.g. Starlink),

and the diffusion of digital booking and information services. Enhanced digital connectivity played a positively associated enabling role, allowing rural tourism actors to maintain market access, reorganize supply chains, and respond flexibly to shifting demand under crisis conditions. However, this interpretation describes a statistical association (correlation), not a proven causal relationship. It remains possible that unobserved factors (e.g. entrepreneurial motivation, external funding) drive both digital adoption and tourism recovery.

Employment in rural tourism and related services demonstrates a consistent upward trend despite the ongoing war. The Service Sector Employment Level Index (SSELI) increased from 15.0 in 2022 to 19.5 in 2024, reflecting job creation in accommodation, agritourism, catering, transport, and auxiliary services. This growth indicates that rural tourism has functioned as an important stabilizing sector for local economies, absorbing labour and supporting income diversification when other economic activities were constrained.

In general, the socio-economic and digital indicators confirm that rural tourism resilience in Transcarpathia has been driven not by a full demographic recovery, but by adaptive restructuring, digitalization, and the strengthening of local tourism networks. These processes underscore the capacity of rural tourism systems to contribute to regional stability and recovery amid prolonged uncertainty.

While remote sensing and digital platform data enable monitoring under crisis conditions, several limitations must be acknowledged. First, spatial resolution constraints: Sentinel-2 imagery (10 m resolution) allows detection of large infrastructure changes but may miss small-scale tourism facilities (e.g. agritourism homesteads). Second, potential biases in satellite data: cloud cover in mountainous regions (the Carpathians) reduced the number of available scenes by approximately 15% in 2022–2023, requiring temporal gap-filling using median compositing, which may smooth over short-term changes. Third, VIIRS night-time light data (NLI) captures economic activity but cannot distinguish between tourism-related and other sources (e.g. military or humanitarian lighting). Fourth, digital platform indicators (TBDI from Booking.com) may overrepresent formal accommodations and underrepresent informal homestays or local booking channels; they also exclude Russian-owned platforms, potentially introducing geopolitical bias. Fifth, official statistics (DRI, SSELI) rely on administrative data that may be incomplete due to population displacement. To mitigate these limitations, all satellite indices

were validated against ground-truth points ($n=150$) with an overall accuracy of 87%, and booking data were cross-checked with national tourism surveys where available. Readers should interpret results with these constraints in mind.

INTEGRATED SUSTAINABLE DEVELOPMENT INDEX (IRSDRT)

Based on the normalized indicators (min–max, 0–100) and the weights defined in the third section, the Integrated Rural Sustainable Development and Resilience Tourism Index (IRSDRT) was calculated as the arithmetic mean of the three sub-indices (I_{ter} , I_{ek} , I_{soc}), with equal weights (1/3 each) reflecting the equal priority of economic, environmental, and social dimensions of sustainable development. IRSDRT increased from 42.45 in 2022 to 53.38 in 2023 and 53.44 in 2024, indicating a rapid post-shock recovery followed by a phase of stabilization rather than continued acceleration. The most pronounced growth occurred in 2023, driven by simultaneous improvements in land-use and infrastructure recovery (I_{ter}), socio-economic and digital resilience (I_{soc}), and environmental sustainability (I_{ek}). As shown in figure 6, I_{ter} increased sharply from 26.64 in 2022 to 44.98 in 2023 but declined slightly in 2024 (40.10), reflecting the completion of priority reconstruction projects and a slowdown in infrastructure expansion. In contrast, I_{ek} exhibited steady growth over the entire period (47.40 $\rightarrow$ 50.92), driven by vegetation recovery, improved water indicators, and the expansion of protected areas. I_{soc} demonstrated the most stable upward trajectory (58.60 $\rightarrow$ 69.30), underlining the critical role of employment growth, digital accessibility, and online tourism services in post-conflict resilience. Figure 6 is a line graph with two vertical axes: the left axis shows the three sub-index values (I_{ter} , I_{ek} , I_{soc} , each 0–100), and the right axis shows the integral IRSDRT (0–100). I_{soc} rises steadily from 58.6 (2022) to 69.3 (2024). I_{ek} increases modestly from 47.4 to 50.9. I_{ter} peaks in 2023 (44.98) then slightly declines to 40.1. IRSDRT follows I_{soc} closely, rising from 42.45 to 53.44, indicating that socio-economic and digital factors drive the overall trend.

Overall, the IRSDRT dynamics confirm that the recovery of rural tourism in Transcarpathia is not linear but characterized by a transition from rapid adaptation to consolidation, with socio-economic and digital factors showing strong statistical associations as potentially dominant long-term drivers. The authors caution that these findings demonstrate correlation, not causation, and that longitudinal data beyond 2024 would be needed to establish causal ordering.

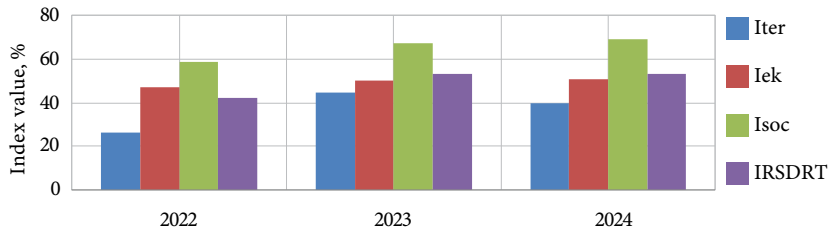


FIGURE 6 Values of I_{ter} , I_{ek} , I_{soc} Sub-Indices, and IRSVRT Integral Index in Transcarpathia

NOTE Temporal dynamics of sub-indices (I_{ter} = Land Use and Infrastructure Index; I_{ek} = Environmental Sustainability Index; I_{soc} = Socio-Economic and Digital Sustainability Index) and the integral IRSVRT in Transcarpathia (2022–2024). I_{soc} shows the most stable upward trajectory (58.6 → 69.3), driving overall IRSVRT growth (42.45 → 53.44). I_{ter} peaks in 2023 (44.98) then declines slightly. I_{ek} increases gradually (47.4 → 50.9). The non-linear pattern of I_{ter} reflects the completion of priority reconstruction projects by 2024. Source: authors' calculations based on table 2 data.

Discussion and Conclusions

DISCUSSION

The results reveal a spatially uneven recovery trajectory of rural tourism in Transcarpathia. Mountainous destinations, particularly the Rakhiv–Yasinia corridor, demonstrate higher growth rates of I_{ter} and I_{soc} , driven by strong natural endowments, the development of agri-tourism estates and eco-trails, and higher levels of digital readiness. The Uzhhorod–Velykyi Bereznyi sub-region also shows positive dynamics, albeit with lower MTCI and TCCI values, indicating incomplete integration of tourism facilities. In contrast, remote rural communities remain high-risk areas, constrained by weak infrastructure recovery, limited digital access, and subdued tourism demand. Three interrelated drivers underpin sustainable rural tourism recovery in the region. First, digitalization (DAI) acts as a catalytic factor by expanding internet coverage and online services, thereby stimulating tourism bookings (TBDI) and supporting cluster formation (TCCI). Second, infrastructure recovery (I_{ter}) directly contributes to employment growth (SSELI) and population return (DRI), reinforcing the socio-economic base of rural destinations. Third, environmental sustainability (I_{ek}) enhances long-term attractiveness, particularly for nature-based and slow tourism, by combining ecosystem preservation (NDVI, RZGCA) with tourism development rather than constraining it.

TABLE 3 Correlation Matrix of Key Sustainability Indices in Transcarpathia (2022–2024)

Variable	I_{ter}	I_{ek}	I_{soc}	DAI	TBDI	SSELI	IRSDRT
I_{ter} (Land use/infrastructure)	1.00						
I_{ek} (Environmental)	0.42*	1.00					
I_{soc} (Socio-economic/digital)	0.68**	0.38*	1.00				
DAI (Digital accessibility)	0.71**	0.35*	0.82***	1.00			
TBDI (Tourism bookings)	0.59**	0.29	0.74**	0.72**	1.00		
SSELI (Tourism employment)	0.63**	0.31	0.69**	0.58**	0.51*	1.00	
IRSDRT (Integrated index)	0.76**	0.55**	0.88***	0.79***	0.73**	0.67**	1.00

NOTE * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Correlations calculated using Pearson's r based on annual values (2022–2024, $n = 3$ years). Given the limited time series, these correlations should be interpreted as exploratory. Analysis performed in R 4.2.

To test Hypothesis H1 (formulated in the Introduction), a correlation analysis was conducted between infrastructural, digital, socio-economic, and environmental indicators. Table 3 presents the correlation matrix.

The IRSDRT exhibits strong positive correlations with I_{ter} , I_{soc} , and DAI, which is consistent with the integrated influence of infrastructure recovery, socio-economic activity, and digital accessibility on overall tourism sustainability. However, correlation does not imply causation. The observed associations could reflect reverse causality (e.g. sustainable tourism attracts digital investment) or confounding factors (e.g. regional economic conditions affect both IRSDRT and its components). The authors therefore present these findings as descriptive associations rather than causal estimates. Infrastructure-related indicators are positively associated with employment growth and cluster development, while digital accessibility shows a strong relationship with both tourism bookings and service-sector employment, underscoring its role as a key resilience mechanism. Environmental indicators demonstrate moderate but consistently positive correlations with infrastructure and socio-economic indices, suggesting that ecological improvements accompany, rather than hinder, post-conflict tourism recovery.

Overall, the correlation structure supports the hypothesis that integrating remote sensing data with geospatial and socio-economic analysis enables effective monitoring of post-conflict rural tourism development, providing a robust empirical basis for data-driven planning and adaptive destination governance.

The findings confirm that integrating remote sensing data with geospatial, socio-economic, and digital indicators enables a dynamic and

multidimensional assessment of sustainable rural tourism development in post-conflict regions (Jovanović and Njeguš 2008; Gan 2023; Jian and Ren 2023; Zhang 2023). Satellite-derived indicators provide an objective basis for monitoring territorial recovery under conditions of data scarcity (Andyana et al. 2023; Li et al. 2012). At the same time, the proposed framework extends existing approaches (Shcherbak, Lyshenko, et al. 2024) by incorporating digital accessibility and socio-digital adaptation processes, which are particularly critical during prolonged crises (Almeida-Santana et al. 2020; Alonso Gallo et al. 2024). The results indicate that tourism recovery in Transcarpathia follows a spatially differentiated and non-linear trajectory. Observed changes in land use and clustering patterns during 2023–2024 suggest the emergence of localized tourism clusters, driven primarily by natural and cultural assets in mountainous rural areas, rather than centralization around urban cores (Morici 2013; Zwierzchowska 2008). This demonstrates that peripheral zones can function as recovery cores, challenging assumptions that post-conflict tourism is inherently urban-centred. Socio-economic dynamics highlight the role of digitalization as a potential resilience mechanism. The positive correlation between digital accessibility and tourism activity ($r = 0.72$, $p < 0.01$) is consistent with the transformative capacity of digital platforms in rural destinations, facilitating coordination, market access, and cluster integration (Almeida-Santana et al. 2020; Tang and Xu 2023; Alonso Gallo et al. 2024). Nevertheless, this evidence is correlational. Alternative explanations include that more prosperous tourism destinations attract investment in digital infrastructure, that reverse causality operates (or: that reverse causality explains the observed association), or that unobserved third variables (e.g., local leadership, external aid) drive both digitalization and tourism growth. Causal claims would require longitudinal panel data or natural experiment designs. Ecological indicators further show that tourism recovery did not compromise environmental integrity; instead, infrastructure development occurred alongside ecosystem stabilization, suggesting that economic recovery and environmental protection can coexist (Gan 2023; Yu 2024).

Overall, the study demonstrates that sustainable rural tourism recovery in post-conflict regions evolves through spatially uneven, digitally mediated adaptation processes. Integrated geospatial monitoring enables early identification of both recovery hotspots and vulnerable peripheral areas, providing a foundation for adaptive and resilient destination governance (Shcherbak, Dorokhova, et al. 2024). A critical reflection on data

reliability is warranted. While the triangulation of satellite, official, and digital platform data strengthens validity, each source has inherent biases. The moderate positive correlations between NLI and TBDI ($r = 0.58$, $p < 0.05$) suggest convergence between economic activity and tourism demand, but the absence of a stronger correlation indicates that NLI captures non-tourism economic activity as well. Similarly, the correlation between DAI and TBDI ($r = 0.72$, $p < 0.01$) supports digitalization as a driver of tourism recovery, but causality cannot be inferred from observational data.

Future research should employ quasi-experimental designs or instrumental variable approaches to establish causal links. Despite these caveats, the consistency of results across multiple independent data sources increases confidence in the main conclusions. The spatially differentiated patterns identified here directly inform the region-specific policy recommendations elaborated in the fifth section.

CONCLUSIONS

This study contributes to tourism and hospitality management literature in three key ways, each clearly distinguished from existing research. First, it reconceptualizes sustainable rural tourism in post-conflict contexts as a dynamic, spatially embedded system, rather than a static outcome measured after recovery. This contrasts with prior post-conflict tourism studies (e.g. Marques et al. 2022; Moric 2013) that have largely relied on retrospective qualitative assessments without real-time spatial monitoring. Second, it advances resilience theory by demonstrating that digital accessibility functions as a mediating dimension linking infrastructure recovery, socio-economic revitalization, and spatial clustering. While previous geospatial studies (e.g. Gan 2023; Jian and Ren 2023) have used remote sensing to measure infrastructure or land-use change, none have empirically identified digitalization as a cross-cutting resilience mechanism in post-conflict rural tourism. This finding extends existing frameworks by adding a fourth (digital) dimension to the traditional economic-environmental-social triad of sustainable tourism. Third, the research positions geospatial analysis not merely as a technical instrument but as a theoretical lens for understanding how sustainability and resilience interact under conditions of prolonged instability. Unlike conventional applications of GIS and remote sensing that focus on descriptive mapping or single-indicator monitoring (Jovanović and Njeguš 2008; Andiyana et al. 2023), this study uses geospatial data to test

a theoretically derived model of multi-dimensional recovery dynamics. By integrating environmental, infrastructural, socio-economic, and digital indicators into a unified framework, the study addresses a persistent gap in tourism theory concerning real-time sustainability assessment in crisis-affected rural destinations.

The findings offer concrete, region-specific actionable insights for destination managers and policymakers in Transcarpathia and comparable post-conflict rural regions.

For Transcarpathia specifically, the following strategies are recommended based on the IRSDRT dynamics and spatial clustering patterns (figs. 3–6):

(1) Prioritize digital infrastructure in lagging corridors. The Digital Accessibility Index (DAI) increased from 70% to 88% regionally, but the Uzhhorod–Velykyi Bereznyi corridor lags behind Rakhiv–Yasinia (DAI 78% vs. 92% in 2024). Policy action: allocate rural broadband funds to western districts (Uzhhorod, Berehove) and subsidize Starlink terminals for remote agritourism estates.

(2) Support cluster formation through shared service hubs. MTCI values remain low for restaurants (0.12–0.35) and hotels (0.18–0.42), indicating fragmented service provision. Action: establish three ‘tourism service hubs’ (Velykyi Bereznyi, Mizhhiria, Yasinia) offering joint booking, waste disposal, and emergency coordination – co-funded by regional budgets (40%) and EU cross-border cooperation programmes (60%).

(3) Protect environmental assets as economic drivers. NDVI and PAGCI improved (28.6 → 36.0 and 10% → 13%), but STCI warming (+1.34°C) threatens lowland zones. Action: designate the Rakhiv–Yasinia corridor as a ‘Sustainable Tourism Zone’ with binding limits on new construction near protected areas (Carpathian Biosphere Reserve) and incentives for reforestation (€500/ha).

(4) Develop crisis-responsive monitoring dashboards. The IRSDRT framework can be operationalized as a quarterly GIS-based dashboard for the Transcarpathian Regional Military Administration, tracking five lead indicators (NLI, TBDI, DAI, NDVI, RSTI) with automated alerts when values drop below 80% of the 2024 baseline.

(5) Target investment to vulnerable peripheral communities. Remote rural areas (e.g. Solotvyno, Vynohradiv) show weak infrastructure recovery (ICI < 5.0) and low digital access (DAI < 70%). Action: direct 30% of regional tourism development funds to these ‘risk zones’ for mobile medical units, waste collection points, and free Wi Fi zones at community centres.

TABLE 4 Summary of Region-Specific Policy Recommendations for Transcarpathia

Priority area	Specific action	Target zone	Timeframe	Responsible actor
Digital infrastructure	Subsidize Starlink terminals for agritourism	Uzhhorod, Berehove districts	2025–2026	Regional Administration + Ministry of Digital Transformation
Cluster formation	Establish three tourism service hubs	Velykyi Bereznyi, Mizhhiria, Yasinia	2025–2027	Tourism Development Agency + EU crossborder programmes
Environmental protection	Create Sustainable Tourism Zone with construction limits	Rakhiv–Yasinia corridor	2025–2030	Ministry of Environment + Carpathian Biosphere Reserve
Monitoring dashboard	Quarterly GISbased IRSDRT dashboard	Regionwide	From Q1 2025	Regional Administration + academic partners
Peripheral investment	Direct 30% of development funds to risk zones	Solotvyno, Vynohradiv	2025–2028	Ministry of Communities and Territories Development

SOURCE Authors’ elaboration based on the study findings.

For other post-conflict regions (e.g. Bosnia, Kosovo, Caucasus), the proposed monitoring framework can be adapted by: (a) adjusting indicator weights to local priorities (e.g. higher environmental weight for biodiversity hotspots), (b) substituting unavailable data sources with alternative satellite platforms (e.g. Landsat for longer time series), and (c) replacing digital platform indicators (TBDI) with mobile network traffic data where booking platforms are less prevalent (table 4).

LIMITATIONS AND FUTURE RESEARCH

Several limitations should be acknowledged.

Remote sensing data constraints: The 10 m spatial resolution of Sentinel-2 may miss small-scale tourism infrastructure (e.g. individual agritourism homesteads), and cloud cover in the Carpathians required temporal compositing that could smooth over rapid changes.

Proxy indicators: VIIRS night-time lights (NLI) are an indirect proxy for economic activity and cannot isolate tourism-specific contributions from military, humanitarian, or other sources.

Digital platform bias: Tourism Booking Development Index (TBDI) data may overrepresent formal accommodations and exclude informal

or locally booked stays; they also reflect geopolitical biases due to the absence of Russian-owned platforms.

Statistical limitations: The correlation analysis (table 3) is based on only three annual observations (2022–2024). While statistically significant correlations were observed, this small sample size means correlations should be interpreted as exploratory descriptive associations rather than robust causal estimates.

Expert weighting: The expert-based determination of indicator weights may introduce subjectivity, although sensitivity analysis confirmed robustness (IRSDRT varied by $< 5\%$ when weights were adjusted by $\pm 20\%$).

Causal interpretation: Throughout the manuscript, we have deliberately used correlational language (e.g., ‘associated with’, ‘consistent with’, ‘reflects’) rather than causal claims. The study design is observational and longitudinal but not experimental; therefore, statements about digitalization ‘driving’ or ‘enabling’ recovery should be understood as empirically grounded hypotheses rather than proven causal mechanisms.

Future studies should (a) integrate higher-resolution remote sensing data (e.g., PlanetScope) and machine-learning algorithms to improve forecasting accuracy; (b) employ quasi-experimental designs, instrumental variables, or difference-in-differences approaches to establish causal links; (c) conduct comparative studies across multiple post-conflict destinations (e.g., Bosnia, Kosovo, Caucasus) to strengthen generalizability; and (d) use data-driven methods such as principal component analysis or analytic hierarchy process to determine indicator weights empirically.

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Vpliv cen nafte in varstva okolja na indijski izvoz nizkoogljičnih tehnologij (LCT) v države OECD: analiza z uporabo gravitacijskega modela

Bhavya Jha and Shrimoyee Ganguly

Ob vse večji zaskrbljenosti glede čezmejnega prenosa čistejših in okolju prijaznejših proizvodov pričujoči članek preučuje, kako nihanja uvoznih cen nafte in izdatki za varstvo okolja v državah OECD vplivajo na indijski izvoz nizkoogljičnih tehnologij (angl. *low-carbon-technology* – LCT), kar je skladno s cilji trajnostnega razvoja (angl. *Sustainable Development Goal* – SDG) 7, 13 in 17. Z uporabo ocenjevalnika Poissonove psevdomaksimalne verjetnosti (Poisson Pseudo Maximum Likelihood – PPML) v okviru strukturnega gravitacijskega modela za 24 držav OECD v obdobju 2002–2021 analiza razkriva asimetrično dinamiko. Naraščanje uvoznih cen nafte pomembno spodbuja indijski izvoz nizkoogljičnih tehnologij, saj povečuje povpraševanje po alternativnih energetskih rešitvah. Nasprotno pa povečani izdatki držav OECD, povezani z varstvom okolja, zmanjšujejo uvoz iz Indije, ker krepijo domače zmogljivosti za proizvodnjo zelenih tehnologij. Ti rezultati postavljajo pod vprašaj splošno uveljavljeno predpostavko, da višji izdatki za varstvo okolja vedno spodbujajo svetovno trgovino s čistimi tehnologijami. Konkurenčnost Indije pri izvozu sončnih fotonapetostnih sistemov, vetrnih tehnologij in komponent za električna vozila (EV) poudarja njen potencial za izkoriščanje strategij diverzifikacije »Kitajska +1« v državah OECD ter spreminjajočih se trgovinskih tokov. Za dolgoročno ohranjanje rasti izvoza nizkoogljičnih tehnologij so ključnega pomena usklajenost politik s cilji trajnostnega razvoja, intenzivnost raziskav in razvoja (R in R) ter večstransko sodelovanje na področju podnebnih ukrepov.

Ključne besede: izvoz nizkoogljičnih tehnologij (LCT), Cilj trajnostnega razvoja 7 (SDG 7), gravitacijski model, države OECD, okoljevarstveni izdatki, uvoz nafte, metoda Poissonove psevdomaksimalne verjetnosti (PPML)

Klasifikacija JEL: C33, F14, F18, Q37, Q56

Managing Global Transitions 24 (3): 313–334

Okoljska trajnostnost in gospodarski razvoj v Srednji Aziji: vloga energije, trgovine in tujih naložb

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Ta raziskava preučuje odnos med emisijami ogljikovega dioksida (CO₂), gospodarsko rastjo, porabo energije, neposrednimi tujimi investicijami in trgovinsko odprtostjo v Kazahstanu, Kirgiški republiki in Uzbekistanu v obdobju 1997–2024. Z uporabo panelnih podatkov Svetovne banke ter metode Pooled Mean Group (PMG) v okviru panelnega modela Autoregressive Distributed Lag (ARDL) analiziramo tako kratkoročno kot dolgoročno dinamiko med izbranimi spremenljivkami. Rezultati kažejo na obstoj dolgoročnega ravnotežnega razmerja med emisijami CO₂ in njihovimi ključnimi ekonomskimi determinantami. Ugotovljeno je, da poraba energije, neposredne tuje investicije in trgovinska odprtost dolgoročno povečujejo emisije CO₂, medtem ko gospodarska rast prispeva k izboljšanju stanja okolja. Ugotovitve poudarjajo prevladujočo vlogo porabe energije pri spodbujanju emisij ter okoljske posledice investicijske in trgovinske integracije. Ti rezultati nakazujejo, da bi morale srednjeazijske države spodbujati uporabo obnovljivih virov energije, izboljševati energetske učinkovitosti ter sprejemati okoljskotrajnostne investicijske in trgovinske politike, da bi dosegle uravnoteženo gospodarsko rast in okoljsko trajnostnost.

Ključne besede: energija, emisije CO₂, gospodarska rast, odprtost trgovine, Srednja Azija

Klasifikacija JEL: Q43, Q56, F18, F21, O44

Managing Global Transitions 24 (3): 335–363

Vplivi pandemije covid-19 na nacionalno gospodarsko blaginjo: kazalnik pristnega napredka za Islandijo

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Pričujoča raziskava ocenjuje gospodarske učinke pandemije covid-19 na Islandiji z uporabo kazalnika pristnega napredka (Genuine Progress Indicator – GPI), alternativnega makroekonomskega merila, ki vključuje okoljske in družbene eksternalije, ki jih bruto domači proizvod (BDP) ne zajema. Raziskava posodablja izračun islandskega GPI za obdobje 2000–2023, pri čemer je glavni poudarek na obdobju pandemije (2019–2023), na podlagi metodologije, ki obsega 28 podkazalnikov. Ključne ugotovitve razkrivajo nasprotujoče si trende. Medtem ko se je BDP v prvem letu pandemije zmanjšal za 6,0 %, je GPI pokazal ohranjanje ravni družbene blaginje. Vladne naložbe v izobraževanje, zdravstvo in infrastrukturo so več kot izravnale povečane družbene stroške

(predvsem zaradi brezposelnosti) ter zmanjšane okoljske stroške (zlasti zaradi manjše porabe neobnovljivih virov in nižjih emisij toplogrednih plinov). Po popolni odpravi potovalnih omejitev leta 2022 in razcvetu turizma sta se oba kazalnika v letih 2022 in 2023 močno okrepila. GPI se je povečal za 12,7 oz. 6,8 %, medtem ko se je BDP povečal za 18,7 oz. 11,0 %. Rezultati kažejo na gospodarsko odpornost Islandije v obdobju krize ter na njeno uspešno okrevanje po pandemiji.

Ključne besede: gospodarska blaginja, alternativno merilo, pristen na-predek, Islandija, pandemija

Klasifikacija JEL: A10, I38

Managing Global Transitions 24 (3): 365–399

Vloga kompetenc za rabo umetne inteligence pri prilagajanju na umetno inteligenco med strokovnjaki za komuniciranje v Omanu

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Tehnologije umetne inteligence (UI) in z njimi povezane kompetence spreminjajo vzorce dela v organizacijah. Zato se morajo strokovnjaki prilagoditi komunikacijskim praksam v organizacijah, ki jih vse bolj oblikuje umetna inteligenca. V naši raziskavi smo preučevali kompetence na področju umetne inteligence med komunikacijskimi strokovnjaki v Omanu. Raziskava je usklajena z vlogo prilagajanja umetni inteligenci v okviru strategije Oman Vision 2040. Izvedli smo anketo med 247 komunikacijskimi strokovnjaki iz sektorjev izobraževanja, bančništva, telekomunikacij, gospodarstva in gradbeništva. Razvili smo merske lestvice za ocenjevanje treh ključnih kompetenc za rabo umetne inteligence: poznavanja umetne inteligence (angl. *AI knowledge*), digitalnih veščin (angl. *digital skills*) in kritičnega mišljenja (angl. *critical thinking* – CI) ter jih empirično preizkusili z uporabo metode modeliranja strukturnih enačb z delnimi najmanjšimi kvadrati (Partial Least Squares Structural Equation Modelling – PLS-SEM). Ugotovitve kažejo, da sta poznavanje umetne inteligence in kritično mišljenje močna napovednika odnosa do umetne inteligence (angl. *AI attitude* – AT). Poleg tega se je izkazalo, da je odnos do umetne inteligence močan neposredni napovednik prilagajanja umetni inteligenci (angl. *AI adaptation* – AD).

Ključne besede: kompetence za rabo umetne inteligence, prilagajanje umetni inteligenci, kritično mišljenje, digitalne veščine, Oman Vision 2040, komunikacijski strokovnjaki

Klasifikacija JEL: O33, D83, J24, M14, O38

Managing Global Transitions 24 (3): 401–432

Spremljanje trajnostnega razvoja ruralnega turizma na pokonfliktnih območjih po konfliktih z uporabo tehnologij daljinskega zaznavanja in geoprostorskih analiz

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Ta študija Pričujoča raziskava preučuje, kako podeželski turizem prispeva k trajnostnemu razvoju, h gospodarskemu okrevanju, k družbeni stabilnosti in ohranjanju kulturne dediščine v pokonfliktnih regijah po konfliktih, pri čemer kot študijo primera za obdobje 2022–2024 uporablja Zakarpatsko regijo oblast v Ukrajini. Uporablja mešani raziskovalni pristop, ki za oceno sprememb rabe zemljišč, obnove infrastrukture, ekološke stabilnosti in družbeno-ekonomske odpornosti združuje satelitsko daljinsko zaznavanje, prostorsko analizo na osnovi GIS ter družbeno-ekonomske kazalnike za oceno sprememb rabe zemljišč, obnove infrastrukture, ekološke stabilnosti in družbeno-ekonomske odpornosti. V nasprotju z obstoječimi geoinformacijskimi študijami raziskavami spremljanja, ki se osredotočajo na posamezne razsežnosti (npr. pokrovnost tal ali turistične tokove) v stabilnih okoljih, naša ta raziskava uvaja teoretično utemeljen, večdimenzionalni okvir, ki povezuje okoljske, infrastrukturne, družbeno-ekonomske in digitalne kazalnike v enoten sestavljeni indeks trajnostnosti. Tak pristop omogoča neprekinjeno spremljanje na območjih, kjer je zbiranje terenskih podatkov omejeno. Ugotovitve kažejo na opazno okrevanje in odpornost regije: infrastruktura, povezana s turizmom, se je močno obnovila, ekološki kazalniki so se sčasoma izboljšali, digitalna dostopnost pa se je znatno povečala, kar podpira razvoj turizma kljub trajajočim izzivom pokonfliktnega obdobja. Raziskava študija predstavlja nov integrirani geoinformacijski okvir za spremljanje trajnostnega prehoda podeželskega turizma na podatkovno omejenih in krizno prizadetih območjih.

Ključne besede: podeželski turizem, pokonfliktno okrevanje, trajnostni razvoj, daljinsko zaznavanje, geoinformacijsko spremljanje.

Klasifikacija JEL: O33, D83, J24, M14, O38

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