“Which dimensions of AI development shape tourism’s direct contribution to GDP? Evidence from a multi-country panel”

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WHICH DIMENSIONS OF AI DEVELOPMENT SHAPE TOURISM'S DIRECT CONTRIBUTION TO GDP? EVIDENCE FROM A MULTI-COUNTRY PANEL

Abstract

Whether national artificial intelligence (AI) ecosystem development shapes tourism's contribution to GDP is an open empirical question, particularly given the multidimensional nature of modern AI ecosystems and the heterogeneous reliance of countries on tourism. This study identifies which dimensions of national AI ecosystem development drive within-country changes in tourism's direct GDP share, using panel data from 33 countries over 2017–2023. Fixed-effects estimation with clustered standard errors is applied to both the composite Stanford HAI AI Vibrancy Score and its seven constituent pillars, complemented by lagged, dynamic, and interaction specifications. The aggregate AI Vibrancy Score shows no significant within-country effect on tourism's GDP share after controlling for macroeconomic factors ($\beta = 0.061$, $p = 0.622$), indicating that overall AI vibrancy alone does not measurably move tourism's economic contribution. The pillar decomposition reveals, however, that this null result masks two significant positive drivers of tourism's GDP share – AI-related R&D ($\beta = 1.811$, $p = 0.005$) and Policy and Governance ($\beta = 0.353$, $p = 0.037$) – both robust to alternative standard errors and two-way fixed effects. The Talent pillar exerts a significant positive effect on tourism's GDP share with a one-year lag ($\beta = 0.183$, $p = 0.025$), indicating that the human-capital channel requires time to materialize. The COVID-19 pandemic reduced tourism's GDP share by approximately 37% ($\beta = -0.455$, $p < 0.001$), and AI development did not moderate this decline. The findings imply that targeted AI policies – particularly in R&D and governance – can strengthen tourism's economic contribution, while aggregate AI metrics obscure heterogeneous pillar-level effects.

Keywords AI development, tourism contribution, panel data, AI vibrancy, pillar decomposition

JEL Classification Z32, O33, C23, L83

INTRODUCTION

Tourism and artificial intelligence (AI) are simultaneously redrawing the contours of the global economy. Tourism's direct contribution reached an estimated USD 3.4 trillion in 2023, approximately 3% of global output (UN Tourism, 2024), with international arrivals recovering to 1.4 billion by 2024 (UN Tourism, 2025) and OECD tourism's direct GDP share rebounding from a pandemic trough toward the pre-COVID 4.4% benchmark (OECD, 2024b). Concurrently, corporate AI investment reached USD 252.3 billion in 2024, 78% of organizations reported using AI, and mentions of AI in national legislation rose ninefold since 2016 across 75 countries (Stanford HAI, 2025). Policy bodies, including the OECD and G7, explicitly frame AI as transformative for tourism through innovation, personalization, and operational efficiency, while flagging adoption costs, data-readiness barriers, and the digital divide

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between large firms and tourism SMEs (OECD, 2024a). Whether, and through which specific channels, national AI ecosystem development shapes tourism's economic contribution at the macro level is therefore a policy question of growing urgency.

The empirical foundations for answering this question are limited in two ways that matter for policy design. First, available macro-level evidence treats AI as a single composite score, leaving open which underlying pillars carry the relationship – R&D, talent, governance, or infrastructure may operate through different channels with different time profiles, and aggregating them can mask economically opposite effects. Second, the most widely used digitalization proxies (internet penetration, e-government indices) are not AI-specific, so they cannot identify whether tourism outcomes respond to general digital readiness or to AI ecosystem development specifically. The resulting aggregation bias limits the design of targeted technology-and-tourism policy mixes – particularly important in the post-COVID phase, where the sector's structural transformation requires differentiated rather than blanket interventions.

The aim of this study is to identify which dimensions of national AI ecosystem development drive within-country changes in tourism's direct contribution to GDP across 33 countries over the 2017–2023 period. The composite Stanford HAI AI Vibrancy Score and its seven constituent pillars – R&D, Economy, Talent, Policy and Governance, Infrastructure, Responsible AI, and Public Opinion – are entered as the explanatory variables in a fixed-effects panel framework with clustered standard errors, complemented by lagged, dynamic, and interaction specifications. Two contributions follow. Methodologically, the disaggregation enables a direct test of which AI ecosystem pillars carry the AI–tourism relationship, separating productivity-enhancement and labor-substitution channels. Substantively, the findings inform policy mixes that target specific AI ecosystem dimensions rather than aggregate AI vibrancy – an actionable distinction for both technology regulators and tourism-sector authorities.

1. LITERATURE REVIEW

The integration of artificial intelligence into tourism and hospitality has attracted considerable scholarly attention. Systematic reviews have identified AI-powered chatbots, predictive analytics, recommendation engines, and service robots as the principal technologies reshaping customer interactions and destination management (Alsharif et al., 2024; Bulchand-Gidumal et al., 2024; Anica-Popa et al., 2025). At the conceptual level, AI technologies have been linked to Sustainable Development Goals related to economic growth and sustainable cities (Dávid & Dadkhah, 2023; Dávid & El Archi, 2024). In applied settings, digital marketing strategies underpinned by AI-driven customer orientation have been shown to predict sustainability outcomes among tourism SMEs in developing economies (Azizov, 2016; Lima et al., 2024; Purnomo et al., 2025), although the G7/OECD policy paper highlighted that such enterprises face disproportionate barriers to adoption related to cost, data readiness, and workforce skills (OECD, 2024a). Despite this growing body of work, the literature remains predominantly qualitative or focused on firm-level technology adoption, offering limited macro-level evidence on how national AI ecosystems shape tourism's aggregate economic contribution.

Moving beyond qualitative assessments, a small but expanding strand of quantitative research has examined the digitalization–tourism nexus using cross-country panel data. Mobile phone subscriptions and broadband access were found to positively affect tourist arrivals and receipts across 123 countries, with stronger effects in developing economies (Sanju et al., 2025), while AI adoption, proxied by startup activity, promoted sustainable tourism growth among leading destinations (Siddik et al., 2025). At the regional level, digital entrepreneurial ecosystem elements have been positively associated with tourism arrivals across the 27 European Union (EU-27) member states (Khatami et al., 2024), and innovation potential driven by digitalization has been identified as a determinant of EU tourism development (Kubickova et al., 2025). In China, smart tourism city development stimulated both growth and employment, although mechanisms differed across urban tiers

(Zheng et al., 2025). However, these studies typically employ broad digitalization proxies rather than AI-specific metrics, and the conceptualization of AI's business value in tourism remains at an early stage (Lee et al., 2026; Streimikiene, 2023). This limitation motivates the use of a disaggregated AI ecosystem measure in the present study.

The question of how AI affects sectoral outcomes is grounded in a broader theoretical debate that focuses on two competing channels: labor substitution, in which automation displaces workers, and productivity enhancement, in which AI augments capabilities and generates efficiency gains. The seminal study on industrial robots in the United States found that each additional robot per thousand workers reduced the employment-to-population ratio by 0.2 percentage points, providing robust evidence for displacement in manufacturing (Acemoglu & Restrepo, 2020). However, global panel analyses using the Stanford HAI AI Vibrancy Index found no significant short-run effect on employment structure or unemployment rates (Kuzior et al., 2025a, 2025c). This discrepancy may reflect differences between physical automation in manufacturing and cognitive AI deployment in services, or the temporal lag required for productivity effects to materialize. The productivity J-curve hypothesis suggests that general-purpose technologies require substantial complementary investments before benefits become observable (Brynjolfsson et al., 2021), and recent cross-country evidence confirms that short-run AI growth effects are concentrated in knowledge-intensive industries within advanced economies with stronger digital infrastructure (Gambacorta et al., 2025; Bagirzade, 2025). These findings suggest that the AI–productivity nexus depends not only on the volume of AI activity but also on specific ecosystem dimensions – a distinction aggregate index may obscure. The question of whether such delayed and heterogeneous effects also characterize the tourism sector is further complicated by the period under study, which coincides with the most severe shock in the sector's modern history.

The COVID-19 pandemic represents precisely such a confounding factor, with estimated cumulative tourism GDP losses of approximately 2.1 trillion USD (Škare et al., 2021). The pandemic has been interpreted not merely as a temporary disruption but as a catalyst for structural transformation toward sustainable tourism models (Gössling et al., 2020), with bibliometric analyses confirming a post-2020 convergence of sustainability, resilience, and digital innovation themes (Kharbanda et al., 2025). Post-pandemic macroeconomic recovery in European economies depended on institutional quality and the rule of law rather than technology variables alone (Vysochyna et al., 2024; Bayar et al., 2023), while digital tools, which have undergone rapid and unpredictable development since the COVID-19 pandemic and remain in demand even after the easing of restrictive measures (Rahmanov et al., 2021), demonstrated potential for real-time tourism monitoring during the crisis (Nagy et al., 2023). Internal demand exhibited heterogeneous responses, with domestic tourism partially compensating for collapsed international arrivals in some economies (Azizov, 2019), and FDI–tourism bidirectional causality was disrupted during the pandemic period (Nikšić Radić & Bogdan, 2024). This evidence underscores the need to control pandemic effects in panel specifications and raises the question of whether AI development can buffer against such structural shocks (Koldovskyi et al., 2025).

The mechanisms linking AI ecosystem development to sectoral performance extend beyond tourism itself, and a broader literature on digital transformation provides relevant complementary insights. Digitalization has been found to strengthen enterprise resilience through e-marketing and environmental flexibility (Chahdi et al., 2025; Elmaghraby et al., 2025) – a finding with clear parallels for tourism firms navigating demand volatility. In healthcare and finance, digitization indicators are positively associated with population well-being (Tossekbayev et al., 2025; Sidii, 2025; Bagirzade, 2024), AI disclosure influences customer behavior in banking (Rao et al., 2025; Sitnicka et al., 2025), and digital enablement is a prerequisite for innovation in insurance (Dillianti et al., 2024; Poorna Chandran & Tholath, 2025), suggesting that AI-driven service innovation generates measurable outcomes where adoption reaches critical mass (Azizov, 2021). At the macroeconomic level, digitalization and FDI jointly drive growth in developed economies (Kusairi et al., 2023), and digital transformation reshapes European economic trajectories (Yarovenko

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et al., 2025a), though sectoral trade composition mediates these effects, with services trade showing a negative short-run association with growth in South Asia (Shaheen & Shuquan, 2025). Government AI readiness correlates positively with energy security (Kuzior et al., 2025b; Kirichok et al., 2025), and convergence in banking digitalization depends on policy orientation rather than income level (Abbasova et al., 2025). Importantly, digitalization also generates risks, including cybercrime escalation (Yarovenko et al., 2025b), smart-city ethics trade-offs (Eik et al., 2026) and financial stratification affecting SMEs during market disruptions (Sartamorn et al., 2025), while quasi-viral technology diffusion theory suggests AI's societal impact depends on alignment with institutional reform (Melnyk et al., 2025). These cross-sectoral findings reinforce the expectation that the AI–tourism nexus operates through multiple, potentially heterogeneous channels requiring disaggregated measurement.

Despite the growing evidence on both AI and tourism separately, critical gaps remain at their intersection. The existing AI–tourism literature is dominated by qualitative and bibliometric studies, with few quantitative analyses employing AI-specific explanatory variables. Studies utilizing the Stanford HAI AI Vibrancy Tool employ the aggregate composite score rather than its constituent pillars, preventing identification of which specific ecosystem dimensions drive sectoral outcomes (Kuzior et al., 2025a; Kirichok et al., 2025). This aggregation bias is problematic given documented heterogeneity in AI ecosystem composition and high inter-pillar correlations. The supply-side mechanisms through which national AI development shapes tourism's economic contribution remain largely unexplored (Sanju et al., 2025), and the competing channels of labor substitution and productivity enhancement have rarely been tested within a unified framework for the tourism sector. This study aims to identify which dimensions of national AI ecosystem development – both the composite AI Vibrancy Score and its seven constituent pillars – drive within-country changes in tourism's direct contribution to GDP across 33 countries over 2017–2023, distinguishing between productivity-enhancement and labor-substitution channels.

2. METHODOLOGY

This study employs panel data analysis to examine the relationship between national AI ecosystem development and the economic contribution of tourism across 33 countries from 2017 to 2023. The estimation proceeds in four stages: aggregate fixed-effects estimation of the composite AI Vibrancy Score; a pillar decomposition into seven AI ecosystem dimensions; lagged and dynamic specifications; and a comprehensive battery of robustness checks.

2.1. Data sources and sample

The dependent variable – tourism's direct contribution to GDP as a percentage of total GDP – is obtained from the UN Tourism database, based on Tourism Satellite Account methodology. Two alternative dependent variables – tourism employment share and tourism gross value added share – are sourced from the OECD Tourism Satellite Account indicators.

The key explanatory variables are derived from Stanford University's Global AI Vibrancy Index (Stanford HAI, 2025), which quantifies national AI ecosystem development across multiple dimensions. The composite AI Vibrancy Score and its seven constituent pillars – Research and Development (R&D), Economy, Talent, Policy and Governance, Infrastructure, Responsible AI, and Public Opinion – serve as the main regressors. Five macroeconomic control variables are sourced from the World Bank's World Development Indicators (World Bank, 2024); a binary COVID-19 indicator (2020–2021) captures the pandemic-induced structural break. Variable definitions and data sources are detailed in Table E1 (Appendix E).

The final analytical sample comprises an unbalanced panel of 33 countries and 169 country-year observations. After dropping observations with missing control variables, the regression sample comprises 166 observations. The full list of countries and their temporal coverage is provided in Appendix A (Table A1).

2.2. Data transformations

The Shapiro-Wilk tests rejected normality for all variables ($p < 0.001$). The Box–Cox test for the dependent variable yielded $\lambda = 0.117$, confirming the appropriateness of a logarithmic transformation; tourism GDP share thus enters as ln(y). The composite AI Vibrancy Score is transformed using log(1 + x) to reduce extreme right skewness (raw: 4.33). GDP per capita is entered in natural logarithmic form. For the seven AI Vibrancy pillars, the Yeo–Johnson transformation was employed to accommodate zero and negative values, effectively reducing skewness across all pillars (e.g., R&D: 4.65 → 0.39; Economy: 4.96 → 0.66).

2.3. Econometric specification

The empirical strategy progresses from aggregate to disaggregate specifications, with model selection guided by the Hausman test and robustness assessed through alternative estimators, variable transformations, and sample restrictions.

Baseline and aggregate models. The preferred specification is a one-way entity fixed effects model that regresses the log-transformed tourism GDP share on the log-transformed AI Vibrancy Score, macroeconomic controls, and a COVID-19 indicator:

$$\ln\left(y_{it}\right) = \alpha_i + \beta \cdot \ln\left(1 + x_{it}\right) + \gamma' Z_{it} + \delta \cdot D_{it} + \varepsilon_{it}, \tag{1}$$

where $Z_{it} = (Z_{1it}, Z_{2it}, Z_{3it}, \ln Z_{4it}, Z_{5it})'$ is a vector of five control variables (FDI/GDP, internet users, trade openness, log GDP per capita, and tertiary enrollment); D_{it} is the COVID-19 dummy; $\boldsymbol{\gamma}$ is a vector of control variable coefficients; and δ captures the average pandemic effect on tourism GDP share. The inclusion of GDP per capita as a control is motivated by the need to isolate the effect of AI development from general economic growth, while FDI and trade openness capture international economic integration channels that may independently affect tourism.

Pillar decomposition. To identify which dimensions of the AI ecosystem drive the aggregate relationship, the composite score is replaced by the individual AI Vibrancy pillars:

$$\ln\left(y_{it}\right) = \alpha_i + \beta_1 P_{1,it} + \beta_2 P_{2,it} + \ldots + \beta_K P_{K,it} + \gamma' Z_{it} + \delta D_{it} + \varepsilon_{it}, \tag{2}$$

where $P_{k,it}$ denotes the Yeo–Johnson-transformed value of pillar k for country i in year t, and β_k is the corresponding pillar-specific coefficient. Three nested models are estimated: Model A with K = 5 pillars (R&D, Economy, Talent, Policy and Governance, Infrastructure); Model B, adding Responsible AI (K = 6, available from 2019); and Model C, including all seven pillars (K = 7, available from 2021). The progressive inclusion strategy addresses the trade-off between information coverage and sample size reduction.

Lagged pillar specification. To capture delayed effects and partially address reverse causality, the contemporaneous pillars are replaced by their one-year lags:

$$\ln\left(y_{it}\right) = \alpha_i + \beta_1 P_{1,i(t-1)} + \ldots + \beta_K P_{K,i(t-1)} + \gamma' Z_{it} + \delta D_{it} + \varepsilon_{it}. \tag{3}$$

The lagged pillars $P_{k,i(t-1)}$ are predetermined relative to the current outcome y_{it}, reducing the risk that contemporaneous feedback drives the estimated associations.

Dynamic and interaction specifications. To account for persistence in tourism GDP shares, a dynamic panel model augments Equation (1) with the lagged dependent variable $\ln(y_{i,t-1})$; the autoregressive coefficient ρ measures the degree of path dependence. With T ≤ 7, this specification is subject to Nickell (1981) bias, and the results are interpreted as indicative. To test whether the AI-tourism relationship is moderated by digital infrastructure or pandemic conditions, interaction specifications are estimated with mean-centered AI Vibrancy and the moderating variable; centering reduces multicollinearity between the interaction term and its constituents.

2.4. Model selection and diagnostic testing

Model selection between FE and RE is governed by the Hausman test. Diagnostic tests include: the Breusch-Pagan and White tests for heteroskedasticity; the Wooldridge test for serial correlation; the Pesaran CD test for cross-sectional dependence; and variance inflation factors (VIF < 10) for multicollinearity. Where heteroskedasticity is detected, standard errors are clustered at the country level (CRV1). HC1 standard errors are reported as an additional robustness check.

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2.5. Robustness checks

The robustness of the main findings is assessed through:

1) alternative standard error estimators (HC1, CRV1, TWFE);
2) dependent variable and AI Score in levels;
3) exclusion of the COVID dummy or COVID years;
4) exclusion of ln GDP per capita;
5) alternative dependent variables (employment share, GVA share); and
6) sub-sample analysis by income group.

2.6. Estimation software

All estimations are conducted in Python 3.12 using pyfixest for fixed-effects regressions, linearmodels for random-effects and the Hausman test, and statsmodels for diagnostic testing.

2.7. Limitations

Several limitations should be acknowledged. First, the panel is unbalanced and relatively short ($T \leq 7$), constraining the reliability of dynamic specifications and precluding System GMM estimation. Second, several AI Vibrancy pillars suffer from data constraints: Responsible AI and Public Opinion are available only from 2019 and 2021, respectively, reducing sample size when included, and near-perfect correlations among R&D, Economy, and Responsible AI (r = 0.97-0.99) inflate standard errors when these pillars enter simultaneously; the preferred five-pillar specification mitigates but does not eliminate this concern. Third, the study identifies within-country associations rather than causal effects; unobserved time-varying confounders cannot be ruled out, and the absence of valid instruments precludes IV estimation. Fourth, the sample is dominated by high-income OECD economies (27 of 33 countries), limiting generalizability to developing economies.

3. RESULTS

The empirical analysis proceeds in five stages: descriptive statistics and variable transformations (Section 4.1), aggregate fixed effects estimation using the composite AI Vibrancy Score (Section 4.2), diagnostic testing (Section 4.3), a pillar decomposition that isolates the effects of individual AI ecosystem dimensions (Section 4.4), and robustness checks including lagged effects, interaction terms, sub-sample analysis, and alternative dependent variables (Section 4.5).

3.1. Descriptive statistics and data transformations

Table 1 reports the descriptive statistics for the main variables across 33 countries and 169 country-year observations spanning 2017–2023. The tourism direct GDP contribution averages 3.29%, with considerable cross-country heterogeneity (SD = 1.92, range: 0.60-9.10%). Countries such as Mexico (mean ≈ 8.5%), Portugal, and Spain exhibit the highest tourism dependency, while Denmark, Israel, and Luxembourg report shares below 1.5% (Appendix F, Figure F5).

The AI Vibrancy Score exhibits pronounced right skewness (4.33) and leptokurtosis (19.14), reflect-

Table 1. Descriptive statistics of main variables (2017–2023)

Variable	N	Mean	SD	Min	Median	Max	Skew.	Kurt.
Tourism GDP share, % (y)	169	3.294	1.920	0.600	2.675	9.100	1.20	0.92
AI Vibrancy Score (x)	169	12.637	12.798	2.370	9.970	78.600	4.33	19.14
FDI, % of GDP	169	−0.481	37.149	−391.56	2.036	234.31	−5.71	83.18
Internet users, %	169	86.861	13.408	18.200	90.425	100.00	−2.70	9.22
Trade openness, %	169	92.103	68.867	23.402	69.609	412.18	2.79	9.14
GDP per capita (US$)	169	40,060	24,922	1,789	41,490	110,873	0.67	0.40
Tertiary enrollment, %	166	70.018	23.413	19.392	73.303	127.58	−0.38	0.04

Note: N = 169 country-year observations, 33 countries, unbalanced panel. GDP per capita in constant 2015 USD.

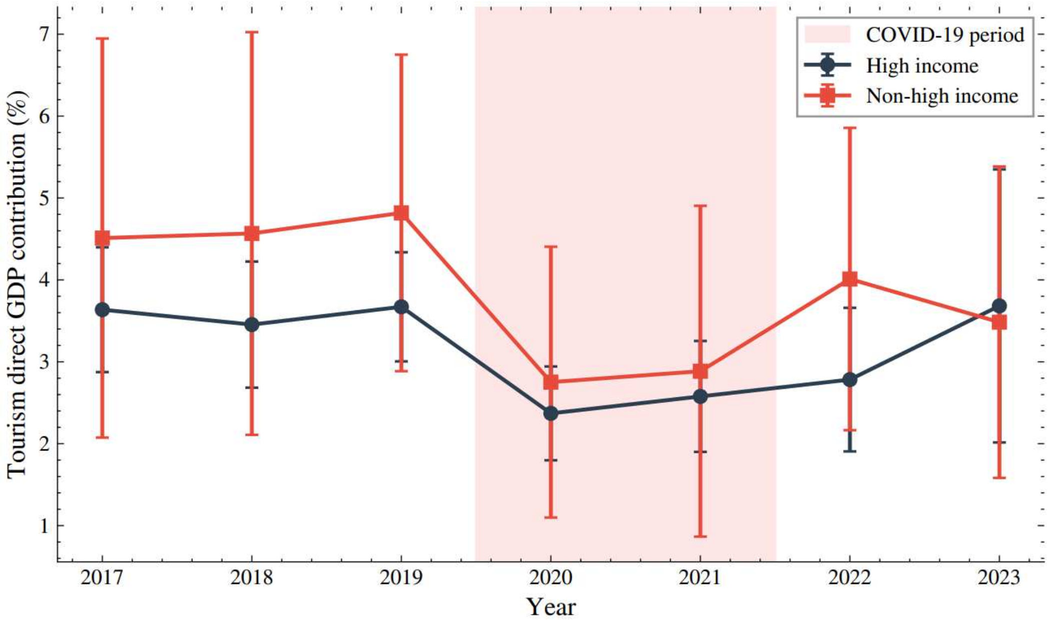

Figure 1. Tourism GDP share dynamics by income group (2017–2023)

ing the dominance of a few AI-frontier economies – notably the United States (mean score: 78.60), which accounts for over six times the sample median of 9.97 (Appendix F, Figure F6). The Shapiro–Wilk tests reject normality for all variables ($p < 0.001$).

The Box-Cox test for the dependent variable yields an optimal parameter $\lambda = 0.117$, close to zero, indicating that a logarithmic transformation is appropriate. The AI Vibrancy Score is transformed using $\log(1 + x)$ to accommodate right skewness while preserving observations near zero. GDP per capita is presented in natural logarithmic form. These transformations enable the interpretation of regression coefficients as approximate elasticities. The seven AI Vibrancy pillars are transformed using the Yeo-Johnson method to reduce skewness and stabilize variance prior to the pillar decomposition analysis.

Figure 1 illustrates the temporal dynamics of tourism GDP share by income group. Both high-income and non-high-income countries experienced a sharp decline during 2020–2021, followed by a partial recovery in 2022–2023. The COVID-19 pandemic represents the dominant structural break in the sample period, which is controlled for through a binary indicator variable equal to one for 2020–2021.

The correlation matrix (Appendix B, Figure B1) reveals a moderate negative pooled correlation between ln(Tourism GDP share) and ln(1 + AI Vibrancy Score) ($r = -0.333$). However, this cross-sectional association is potentially confounded by income level, as high-AI countries tend to have more diversified economies with lower tourism dependence. The variance inflation factors (VIF) are all below 3.4 (maximum: ln GDP per capita, VIF = 3.39), confirming the absence of severe multicollinearity among the regressors (Table B1).

3.2. Aggregate AI Vibrancy Score: fixed effects estimation

Table 2 presents the fixed effects regression results for three specifications. The baseline model (M1), which includes only entity fixed effects and no controls, yields a statistically significant negative coefficient on the AI Vibrancy Score ($\beta = -0.303$, $p = 0.003$). This negative within-country association is noteworthy but potentially misleading: once macroeconomic controls are included (M2), the coefficient changes sign and becomes statistically insignificant ($\beta = 0.061$, $p = 0.622$). This reversal indicates that the apparent negative association in M1 reflects omitted variable bias – countries that experienced rapid AI development during this period simultaneously underwent structural economic changes captured by the control vari-

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Table 2. Fixed effects regression results: aggregate AI Vibrancy Score

Variable	M1 (FE)	M2 (FE + controls)	M3 (TWFE)
ln(1 + AI Vibrancy)	−0.303** (0.093)	0.061 (0.121)	0.225 (0.145)
FDI, % of GDP		0.001*** (0.000)	0.000* (0.000)
Internet users, %		−0.008 (0.010)	−0.003 (0.010)
Trade openness, %		−0.005 (0.004)	−0.002 (0.003)
ln(GDP per capita)		0.647 (0.908)	1.214 (1.226)
Tertiary enrollment, %		−0.001 (0.006)	−0.001 (0.006)
COVID dummy		−0.455*** (0.076)	
Country FE	x	x	x
Year FE	–	–	x
Observations	163	163	163
R^2 (within)	0.735	0.870	0.878

Note: Dependent variable: ln(Tourism GDP share, %). Standard errors clustered by country (CRV1) in parentheses. Significance: *** p < 0.001, ** p < 0.01, * p < 0.05.

ables. The two-way fixed effects specification (M3), which additionally absorbs common year shocks, produces a positive but insignificant coefficient ($\beta = 0.225$, $p = 0.130$).

The within R^2 increases substantially from M1 (0.735) to M2 (0.870), confirming the explanatory power of the macroeconomic controls. The COVID-19 dummy is the single strongest predictor across all specifications ($\beta = -0.455$, $p < 0.001$ in M2), corresponding to an approximate 36.6% decline in tourism GDP share during the pandemic years (calculated as $\exp(-0.455) - 1$). FDI as a share of GDP is also consistently significant ($\beta = 0.001$, $p < 0.001$ in M2). Figure 2 visualizes the coefficient estimates and 95% confidence intervals for the AI Vibrancy variable across the main and extended specifications.

The Hausman test (Table 3) rejects the null hypothesis of no systematic difference between the FE and RE estimators ($\chi^2 = 14.55$, $df = 7$, $p = 0.042$), confirming that the fixed effects specification is preferred. In the RE model, the AI Vibrancy coefficient is negative but insignificant ($\beta = -0.095$, $p = 0.246$), while the FE estimate is positive and insignificant ($\beta = 0.061$, $p = 0.622$). The divergence reflects the correlation between unobserved country heterogeneity and the regressors, as anticipated by the Hausman test result.

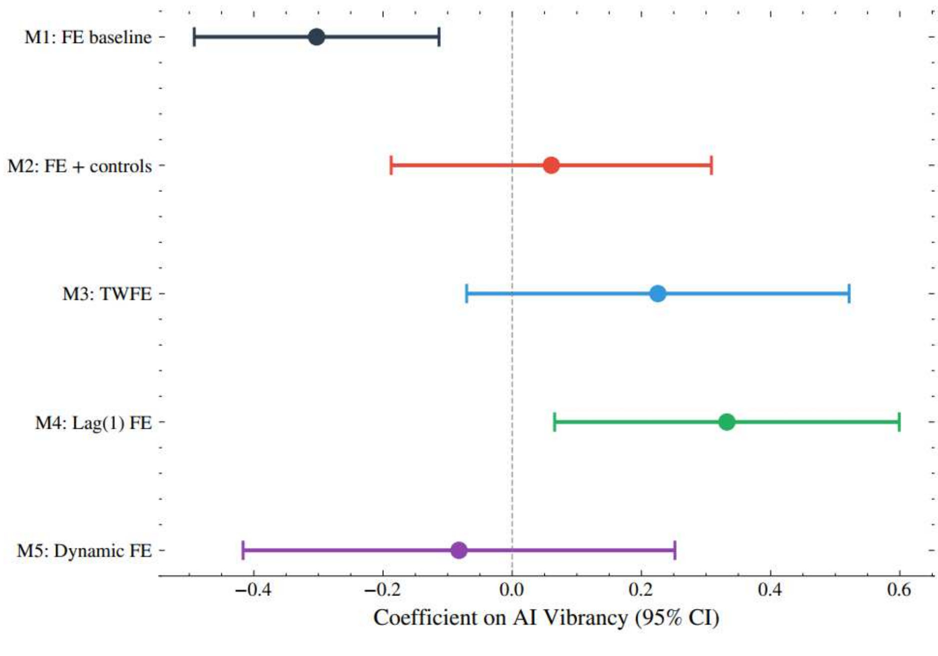

Figure 2. Effect of AI Vibrancy on ln(Tourism GDP share) across model specifications

Table 3. FE vs RE comparison and Hausman test

Variable	FE Coefficient (t-stat)	RE Coefficient (t-stat)
ln(1 + AI Vibrancy)	0.061 (0.506)	−0.095 (−1.164)
FDI, % of GDP	0.001 (4.228)	0.001 (7.000)
Internet users, %	−0.008 (−0.837)	−0.005 (−0.775)
Trade openness, %	−0.005 (−1.228)	−0.001 (−0.374)
ln(GDP per capita)	0.647 (0.723)	−0.015 (−0.099)
Tertiary enrollment, %	−0.001 (−0.227)	0.003 (0.633)
COVID dummy	−0.455 (−6.063)	−0.452 (−7.085)
R^2 (within / overall)	0.531	0.225
Hausman χ^2 (df = 7)		14.55 (p = 0.042)

Note: T-statistics in parentheses. Hausman test rejects H0 at 5%, indicating FE is preferred.

Table 4. Diagnostic tests for the FE model (M2)

Test	Statistic	p-value	Conclusion
Breusch-Pagan	LM = 24.356	0.001	Heteroskedasticity
White	LM = 80.339	< 0.001	Heteroskedasticity
Durbin-Watson (pooled)	DW = 0.634	–	Positive AC (pooled)
Wooldridge (FE serial corr.)	F = 1.318	0.254	No serial correlation
Pesaran CD	CD = 0.056	0.955	Independence

Note: Breusch–Pagan and White tests based on pooled OLS residuals. Wooldridge test based on first-differenced FE residuals. Pesaran CD test based on pairwise cross-sectional correlation of FE residuals.

3.3. Diagnostic tests

Table 4 summarizes the diagnostic tests for the preferred FE specification (M2). The Breusch-Pagan (LM = 24.36, p = 0.001) and White (LM = 80.34, p < 0.001) tests confirm the presence of heteroskedasticity, necessitating the use of robust standard errors. The Durbin–Watson statistic from pooled OLS (DW = 0.634) suggests positive autocorrelation; however, the panel-specific Wooldridge test for serial correlation in the FE idiosyncratic errors does not reject the null (F = 1.32, p = 0.254), indicating that serial correlation is not a material concern within the FE framework. The Pesaran CD test reveals no cross-sectional dependence (CD = 0.056, p = 0.955), suggesting that unobserved common shocks are adequately absorbed by the year controls and COVID dummy. Given these results, standard errors clustered at the country level (CRV1) provide appropriate inference correction throughout the analysis.

3.4. Pillar decomposition: heterogeneous effects of AI ecosystem dimensions

The insignificance of the aggregate AI Vibrancy Score may mask the opposing effects of its constituent dimensions. To test this hypothesis, the composite score is replaced by the individual AI Vibrancy pillars. Table 5 reports the descriptive statistics for the seven pillars. R&D (mean = 1.88,

Table 5. Descriptive statistics of AI Vibrancy pillars (raw values)

Pillar	N	Mean	SD	Min	Median	Max	Skew.
R&D	169	1.885	4.656	0.01	0.55	29.69	4.65
Economy	169	1.242	4.340	0.00	0.17	25.00	4.96
Talent	169	6.006	2.079	1.90	5.85	13.86	0.85
Policy & Governance	169	0.850	1.225	0.00	0.25	6.25	2.04
Infrastructure	169	1.879	2.647	0.00	0.98	12.99	2.68
Responsible AI	119	0.322	1.028	0.00	0.04	5.88	4.99
Public Opinion	59	1.623	0.758	0.03	1.55	3.72	0.42

Note: Responsible AI available from 2019, Public Opinion from 2021.

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SD = 4.66) and Economy (mean = 1.24, SD = 4.34) exhibit extreme right skewness (4.65 and 4.96, respectively), driven by the United States, which dominates both dimensions (Appendix F, Figure F2). Talent is the most evenly distributed pillar (mean = 6.01, skewness = 0.85), while Responsible AI (available from 2019) and Public Opinion (available from 2021) have substantial missing data. All pillars are transformed using the Yeo-Johnson method prior to estimation.

The inter-pillar correlation matrix (Appendix F, Figure F1) reveals very high correlations among R&D, Economy, and Responsible AI (r = 0.97-0.99), reflecting the concentration of all three dimensions in the same AI-frontier economies. In contrast, Talent is essentially uncorrelated with R&D (r = –0.04) and Economy (r = –0.00), suggesting that human capital in AI operates independently of commercial and research intensity. Policy and Governance correlate moderately with R&D (r = 0.63) and Infrastructure (r = 0.55). These correlation patterns inform the specification strategy: the preferred model (Model A) includes only five pillars with complete data coverage and manageable collinearity, while the extended models (B and C) serve as sensitivity checks.

Table 6 reports the pillar decomposition results. The preferred specification (Model A: 5 pillars, N = 163, R^2 = 0.88, R^2 within = 0.566) reveals two statistically significant within-country effects that were concealed by the aggregate score.

The R&D pillar exhibits a strong positive association with tourism GDP share (β = 1.811, SE = 0.603, p = 0.005). This indicates that countries experiencing within-country growth in AI-related research and development simultaneously witness an increase in tourism's economic contribution, consistent with the productivity-enhancement channel hypothesized in the introduction. The Policy and Governance pillar is also positively significant (β = 0.353, SE = 0.162, p = 0.037), suggesting that proactive government engagement with AI – through regulation, national AI strategies, and public investment – is associated with enhanced tourism sector performance.

The remaining pillars do not reach conventional significance thresholds in the contemporaneous specification. Talent approaches significance with a negative sign (β = –0.071, p = 0.111), which may reflect the short-run labor reallocation effects of AI skill accumulation away from tourism-intensive occupations. Economy and Infrastructure are statistically insignificant, and Responsible AI (Model B) and Public Opinion (Model C) are also insignificant, though these results are constrained by reduced sample sizes and high collinearity.

Table 6. Fixed effects regressions with AI Vibrancy pillars (Yeo-Johnson transformed)

Variable	Model A (5 pillars)	Model B (6 pillars)	Model C (7 pillars)
R&D	1.811** (0.603)	1.270 (1.098)	–2.158 (2.697)
Economy	0.476 (0.580)	0.911 (0.606)	0.007 (0.713)
Talent	–0.071 (0.043)	–0.144 (0.104)	–0.552* (0.236)
Policy & Governance	0.353* (0.162)	0.311 (0.364)	0.302 (0.364)
Infrastructure	0.022 (0.167)	0.074 (0.194)	0.297 (1.058)
Responsible AI		–0.116 (1.251)	–1.721 (1.984)
Public Opinion			0.351 (0.373)
FDI, % of GDP	0.001*** (0.000)	0.000. (0.000)	–0.000 (0.001)
Internet users, %	–0.008 (0.010)	–0.018 (0.013)	0.018 (0.030)
Trade openness, %	–0.002 (0.004)	–0.004 (0.006)	0.011 (0.012)
ln(GDP per capita)	0.423 (0.835)	2.044 (1.209)	8.816. (4.464)
Tertiary enrollment	0.000 (0.005)	–0.004 (0.004)	–0.009 (0.006)
COVID dummy	–0.478*** (0.104)	–0.452*** (0.122)	–0.364. (0.204)
Country FE	x	x	x
Observations	163	113	50
R^2	0.880	0.889	0.957
R^2 (within)	0.566	0.571	0.762

Note: Dependent variable: ln(Tourism GDP share, %). Standard errors clustered by country (CRV1) in parentheses. Pillars are Yeo-Johnson transformed. Models B and C have fewer observations due to missing Responsible AI (2017–2018) and Public Opinion (2017–2020) data. Significance: *** p < 0.001, ** p < 0.01, * p < 0.05, p < 0.10.

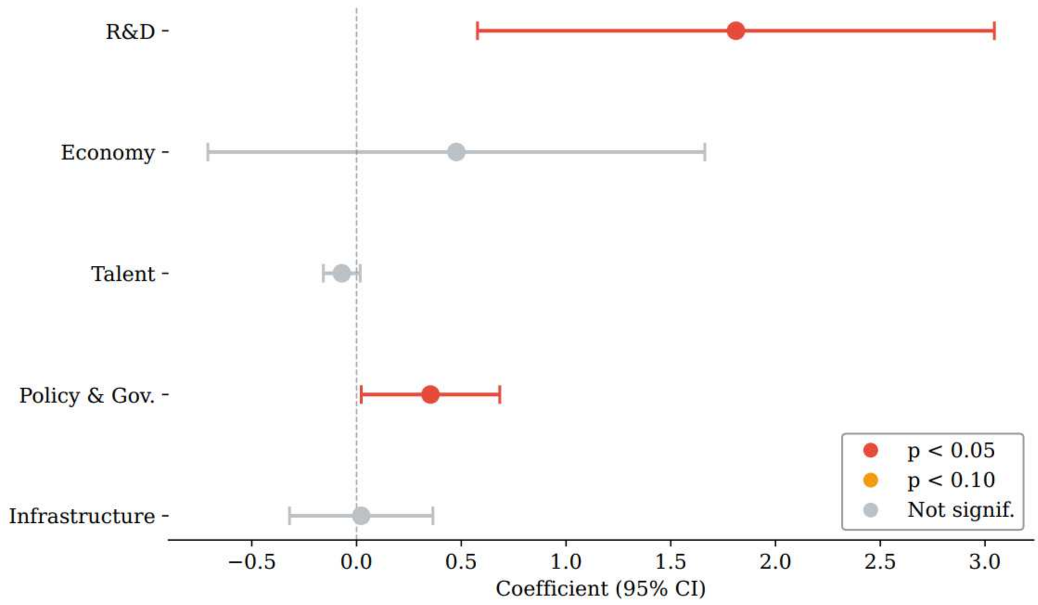

Figure 3. AI Vibrancy pillar effects on ln(Tourism GDP share)

Figure 3 visualizes the pillar coefficients and their 95% confidence intervals from Model A, clearly distinguishing the significant effects of R&D (red) and Policy and Governance (yellow) from the insignificant remaining pillars (grey).

The instability of R&D in Models B and C (β = 1.270, p = 0.257 in Model B; β = –2.158, p = 0.433 in Model C) is attributable to the near-perfect collinearity between R&D and Responsible AI (r = 0.97) and R&D and Economy (r = 0.97). The five-pillar specification (Model A) thus represents the most reliable decomposition, balancing parsimony with coverage.

Figure F2 (Appendix F) displays the mean pillar scores by country, confirming the extreme concentration of AI R&D and Economy in the United States, Japan, the United Kingdom, and India. Figure F3 (Appendix F) compares the AI pillar profiles of the top-5 and bottom-5 countries by tourism GDP share, revealing that tourism-intensive economies (Mexico, Portugal, Spain) tend to have lower AI R&D but higher Policy and Governance scores relative to low-tourism economies.

3.5. Robustness checks

The robustness of the main findings is assessed through several dimensions: alternative standard errors, two-way fixed effects, lagged specifications, interaction terms, sub-sample analysis, alternative dependent variables, and exclusion of the COVID period.

Alternative standard errors and TWFE. Table 7 reports the pillar decomposition under alternative inference methods. Under heteroskedasticity-robust standard errors (HC1), R&D remains significant (β = 1.811, p = 0.003) with a narrower confidence interval, and Policy and Governance retains significance (β = 0.353, p = 0.019). Under two-way fixed effects (TWFE), R&D remains highly significant (β = 1.657, p = 0.009) and Policy and Governance retains marginal significance (β = 0.306, p = 0.051). The consistency of R&D across all three inference methods (CRV1: p = 0.005; HC1: p = 0.003; TWFE: p = 0.009) provides strong evidence that this result is not an artefact of the error structure.

Lagged pillar effects. The lagged specification, in which pillar scores at t − 1 predict tourism GDP share at t, yields an additional finding: the Talent pillar becomes positively significant with a one-year lag (β = 0.183, SE = 0.077, p = 0.025), whereas its contemporaneous effect was negative and insignificant (β = –0.071, p = 0.111). This sign reversal is economically interpretable: the within-country accumulation of AI talent may initially

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Table 7. Robustness checks for the pillar model (selected coefficients)

Pillar	FE (CRV1)	FE (HC1)	TWFE	Lag(1) FE
R&D	1.811**	1.811**	1.657**	1.256
Economy	0.476	0.476	0.311	0.922
Talent	−0.071	−0.071	−0.024	0.183*
Policy & Gov.	0.353*	0.353*	0.306.	0.310
Infrastructure	0.022	0.022	0.201	−0.015
COVID dummy	−0.478***	−0.478***	(absorbed)	−0.496***
Observations	163	163	163	133

Note: Significance stars based on respective p-values. Lag(1) specification uses pillar values at t – 1 with controls at t. TWFE absorbs the COVID dummy through year fixed effects.

divert human capital from service-oriented sectors (including tourism), but with a one-year delay, the acquired skills are deployed to develop tourism-enhancing applications, digital services, and efficiency improvements. Meanwhile, the lagged R&D effect loses formal significance ($\beta = 1.256$, $p = 0.108$), suggesting that R&D operates primarily through contemporaneous channels rather than delayed diffusion.

Interaction terms. The interaction between AI Vibrancy and internet penetration (centered) is statistically insignificant ($p > 0.10$), indicating that the effect of AI on tourism does not vary with the level of digital infrastructure. Similarly, the AI × COVID interaction is insignificant ($p > 0.10$), suggesting that higher AI development did not mitigate the pandemic-induced decline in tourism GDP share.

Income group sub-samples. The sample includes 27 high-income countries (130 observations) and 6 non-high-income countries (36 observations). While the limited size of the non-high-income sub-sample restricts statistical power, the general patterns are consistent across groups, with COVID remaining the dominant predictor in both sub-samples.

Dynamic specification. The dynamic FE model with a lagged dependent variable (Table D1, Appendix D) confirms strong persistence in tourism GDP shares ($\beta\_y(t–1) = 0.248$, $p < 0.01$). The AI Vibrancy coefficient remains insignificant in the dynamic specification ($\beta = –0.082$, $p > 0.10$), consistent with the static FE results. Given the short time dimension ($T \leq 7$), the dynamic FE estimates are subject to Nickell (1981) bias, and the results should be interpreted as indicative rather than definitive.

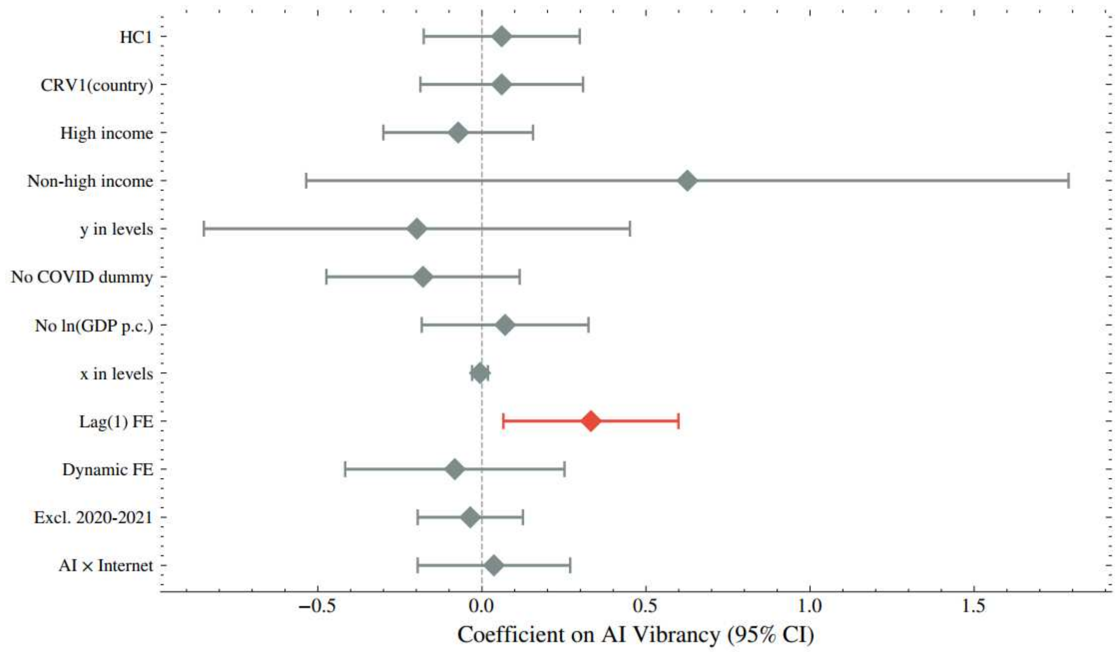

Figure 4. Robustness of the AI Vibrancy coefficient across specifications

Alternative dependent variables. The aggregate AI Vibrancy Score produces insignificant coefficients when estimated against tourism employment share (OECD, N = 131; β = –0.036, p = 0.79) and tourism GVA share (OECD, N = 126; β = –0.098, p = 0.18), consistent with the main GDP share results.

Exclusion of the COVID years. Removing 2020–2021 from the sample (N = 111) does not alter the substantive conclusions for the aggregate AI Vibrancy variable. Figure 4 synthesizes the AI coefficient estimates and confidence intervals across all robustness specifications, confirming the null result for the aggregate score and the stability of the baseline estimates.

Figure F4 (Appendix F) further illustrates the COVID-19 impact through a box plot of tourism GDP share distributions across pre-pandemic (2017–2019), pandemic (2020–2021), and post-pandemic (2022–2023) periods. The median tourism GDP share declined from approximately 3.5% pre-COVID to 2.0% during the pandemic, with a partial recovery to 2.8% in the post-pandemic period.

Country-level fixed effects (Appendix C, Table C1 and Figure C1) reveal substantial heterogeneity in baseline tourism dependency after controlling for all observables. Portugal, Spain, and Mexico exhibit the largest positive fixed effects, consistent with their structural orientation toward tourism. The spaghetti plot (Appendix F, Figure F5) confirms the asymmetric COVID recovery pattern, with tourism-dependent economies experiencing both deeper declines and more pronounced recoveries.

3.6. Summary of findings

The results support three main conclusions. First, the aggregate AI Vibrancy Score does not exert a statistically significant within-country effect on tourism's contribution to GDP once macroeconomic controls are included (β = 0.061, p = 0.622 in the preferred FE specification). This null result, however, conceals heterogeneous effects of individual AI ecosystem dimensions.

Second, the pillar decomposition reveals that AI-related R&D intensity (β = 1.811, p = 0.005) and government AI policy engagement (β = 0.353, p = 0.037) are positively and significantly associated with tourism GDP share within countries over time. These results are robust to alternative standard error estimators (HC1: p = 0.003 and p = 0.019) and two-way fixed effects (TWFE: p = 0.009 and p = 0.051), supporting the productivity-enhancement channel hypothesized in the introduction.

Third, the AI Talent pillar exhibits a significant positive effect with a one-year lag (β = 0.183, p = 0.025), suggesting that the human capital channel in AI requires time to materialize as trained professionals develop and deploy tourism-enhancing applications. The COVID-19 pandemic remains the dominant structural shock, reducing tourism GDP share by approximately 37% (β = –0.478, p < 0.001), and AI development did not moderate this effect.

These findings should be interpreted with the caveat that the unbalanced panel (33 countries, 166 observations, T ≤ 7) limits the scope for dynamic and causal inference, and the high inter-pillar collinearity (r up to 0.97) constrains the simultaneous estimation of all seven AI ecosystem dimensions.

4. DISCUSSION

The central finding – that the aggregate AI Vibrancy Score shows no statistically significant within-country effect on tourism GDP share (β = 0.061, p = 0.622) – is consistent with global panel evidence that composite AI metrics do not produce detectable short-run sectoral effects (Kuzior et al., 2025a) and with the argument that general-purpose technologies require complementary investments before productivity benefits materialize (Brynjolfsson et al., 2021; OECD, 2024a). This appears to contradict studies reporting positive effects of digitalization on tourist arrivals (Sanju et al., 2025), but the discrepancy likely reflects differences in measurement – narrow proxies versus a composite index whose dimensions may exert opposing effects. The pillar decomposition resolves this contradiction: the null aggregate masks two significant positive drivers, R&D and Policy and Governance, offset by insignificant contributions of other dimensions (Asare, 2026). The R&D effect

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(β = 1.811, p = 0.005) likely operates through AI-enabled service innovation – personalized recommendations, dynamic pricing, automated customer service – enhancing value-added intensity (Bulchand-Gidumal et al., 2024), with the channel potentially being scale-dependent (Kritikos et al., 2025). The Policy and Governance effect (β = 0.353, p = 0.037) indicates that proactive government AI engagement creates an enabling environment, consistent with evidence that institutional quality determines digital transformation outcomes more than infrastructure or income levels (Abbasova et al., 2025; Vysochyna et al., 2024), while growing attention to AI's distributional consequences is reflected in the emerging discourse on fiscal instruments for automation (Furgasė & Miceikienė, 2025).

The delayed positive effect of the Talent pillar (β = 0.183, p = 0.025 with a one-year lag, versus an insignificant contemporaneous estimate) provides empirical support for the productivity J-curve hypothesis (Brynjolfsson et al., 2021). AI-skilled professionals need time to develop sector-specific applications such as AI-powered travel planning and accessibility solutions (Gavurova & Polishchuk, 2025), and the translation of talent into sectoral outcomes depends on institutional support for workforce transition (Yarovenko et al., 2024). In contrast to the displacement effects of industrial robots in manufacturing (Acemoglu & Restrepo, 2020), the lagged positive effect suggests that AI-related human capital in tourism operates through augmentation rather than substitution – consistent with evidence that AI enhances workers in non-routine service tasks (OECD, 2024a) and that targeted AI applications predict innovation in customer-facing industries (Awad, 2024).

The COVID-19 dummy emerges as the single most powerful predictor, reducing tourism GDP share by approximately 37% (β = −0.455, p < 0.001) – consistent with estimated cumulative losses of 2.1 trillion USD (Škare et al., 2021) and the characterization of the pandemic as a structural break requiring a tourism growth model reset (Gössling et al., 2020). The finding that AI development did not moderate this decline likely reflects the supply-side nature of the shock – travel restrictions that digital technologies could not circumvent – rather than the irrelevance of AI for tourism resilience. The pandemic nonetheless accelerated AI adoption in hospitality (Bulchand-Gidumal et al., 2024), suggesting that longer-term productivity effects may emerge as the post-pandemic period extends.

CONCLUSION

This paper sought to identify which dimensions of national AI ecosystem development drive within-country changes in tourism's economic contribution, disaggregating the composite AI Vibrancy Score into its constituent pillars. The analysis employed fixed effects panel estimation on an unbalanced panel of 33 countries over 2017–2023 (166 observations), complemented by lagged, dynamic, and interaction specifications.

The aggregate AI Vibrancy Score shows no significant within-country effect after introducing macroeconomic controls (β = 0.061, p = 0.622). The pillar decomposition reveals two significant positive drivers: R&D (β = 1.811, p = 0.005) and Policy and Governance (β = 0.353, p = 0.037), both robust to alternative standard errors and two-way fixed effects. The Talent pillar becomes significant with a one-year lag (β = 0.183, p = 0.025), while the COVID-19 pandemic reduced tourism GDP share by approximately 37% (β = −0.478, p < 0.001), and AI development did not moderate this decline.

These findings carry three policy implications. First, governments should prioritize AI-related R&D to enhance tourism productivity, particularly in upper-middle-income economies such as Mexico, Turkey, and Malaysia, which may benefit from dedicated AI–tourism R&D programs. Second, the Policy and Governance effect underscores that institutional frameworks – national AI strategies incorporating tourism digitalization and cross-ministerial coordination – are essential for translating technological potential into sectoral outcomes; digital infrastructure alone is insufficient. Third, the lagged Talent effect highlights the need for medium-term workforce development, including AI literacy programmes for hospitality professionals and interdisciplinary curricula at the intersection of AI and tourism management.

These conclusions should be interpreted within the study's limitations: short time dimension (T ≤ 7) constraining causal inference and sample dominance by high-income OECD economies restricting generalizability. Future research should expand the temporal coverage, incorporate sub-pillar indicators, and employ instrumental variable strategies to identify causal effects.

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Writing – review & editing: Farhad Rahmanov, Anar Azizov, Elnara Samedova, Murad Bagirzadeh, Gunel Isayeva, Taleh Aghazada, Abdulla Abdullayev.

DATA AVAILABILITY

All data used in this study are publicly available from the Stanford HAI Global AI Vibrancy Tool, UN Tourism, the OECD Tourism Satellite Account, and the World Bank World Development Indicators.

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APPENDIX A. List of countries in the panel

Table A1. Countries included in the sample, with income group, region, and temporal coverage

No.	ISO3	Country	Income group	Region	Obs	Period
1	AUS	Australia	High income	East Asia & Pacific	7	2017–2023
2	AUT	Austria	High income	Europe & Central Asia	4	2018–2021
3	BEL	Belgium	High income	Europe & Central Asia	4	2019–2022
4	CAN	Canada	High income	North America	7	2017–2023
5	CHE	Switzerland	High income	Europe & Central Asia	7	2017–2023
6	DEU	Germany	High income	Europe & Central Asia	5	2017–2021
7	DNK	Denmark	High income	Europe & Central Asia	6	2017–2022
8	ESP	Spain	High income	Europe & Central Asia	5	2017–2021
9	EST	Estonia	High income	Europe & Central Asia	1	2017
10	FIN	Finland	High income	Europe & Central Asia	6	2017–2022
11	FRA	France	High income	Europe & Central Asia	4	2019–2022
12	GBR	United Kingdom	High income	Europe & Central Asia	4	2017–2020
13	IND	India	Lower middle income	South Asia	6	2017–2022
14	IRL	Ireland	High income	Europe & Central Asia	1	2019
15	ISR	Israel	High income	Middle East & N. Africa	7	2017–2023
16	ITA	Italy	High income	Europe & Central Asia	2	2017–2019
17	JPN	Japan	High income	East Asia & Pacific	6	2017–2022
18	KOR	South Korea	High income	East Asia & Pacific	1	2019
19	LUX	Luxembourg	High income	Europe & Central Asia	6	2017–2022
20	MEX	Mexico	Upper middle income	Latin America & Carib.	6	2017–2022
21	MYS	Malaysia	Upper middle income	East Asia & Pacific	7	2017–2023
22	NLD	Netherlands	High income	Europe & Central Asia	7	2017–2023
23	NOR	Norway	High income	Europe & Central Asia	5	2017–2021
24	NZL	New Zealand	High income	East Asia & Pacific	7	2017–2023
25	POL	Poland	High income	Europe & Central Asia	3	2018–2022
26	PRT	Portugal	High income	Europe & Central Asia	7	2017–2023
27	RUS	Russia	Upper middle income	Europe & Central Asia	7	2017–2023
28	SAU	Saudi Arabia	High income	Middle East & N. Africa	7	2017–2023
29	SWE	Sweden	High income	Europe & Central Asia	5	2017–2021
30	TUR	Turkey	Upper middle income	Europe & Central Asia	4	2019–2022
31	ARE	United Arab Emirates	High income	Middle East & N. Africa	3	2019–2021
32	USA	United States	High income	North America	6	2017–2022
33	ZAF	South Africa	Upper middle income	Sub-Saharan Africa	6	2017–2022

Note: Income groups follow World Bank classification. Total: 169 country–year observations; 27 high-income, 5 upper-middle-income, and 1 lower-middle-income country. Panel is unbalanced due to varying AI Vibrancy Index data availability.

APPENDIX B. Correlation matrix

Table B1. Pairwise correlation coefficients (regression sample, N = 166)

	ln(Tour. GDP)	ln(1+AI)	FDI	Internet	Trade	ln(GDP)	Tert.
ln(Tourism GDP share)	1.000						
ln(1 + AI Vibrancy)	−0.333	1.000					
FDI/GDP	0.123	−0.050	1.000				
Internet users	−0.185	0.176	−0.055	1.000			
Trade openness	−0.182	−0.075	−0.241	0.280	1.000		
ln(GDP per capita)	−0.183	0.282	−0.090	0.786	0.342	1.000	
Tertiary enrollment	0.137	0.108	0.090	0.412	−0.343	0.421	1.000

Note: All variables are in their transformed form as used in the regressions. The highest correlation among independent variables is between Internet users and ln(GDP per capita) (r = 0.786). VIF values are all below 3.4, confirming no severe multicollinearity.

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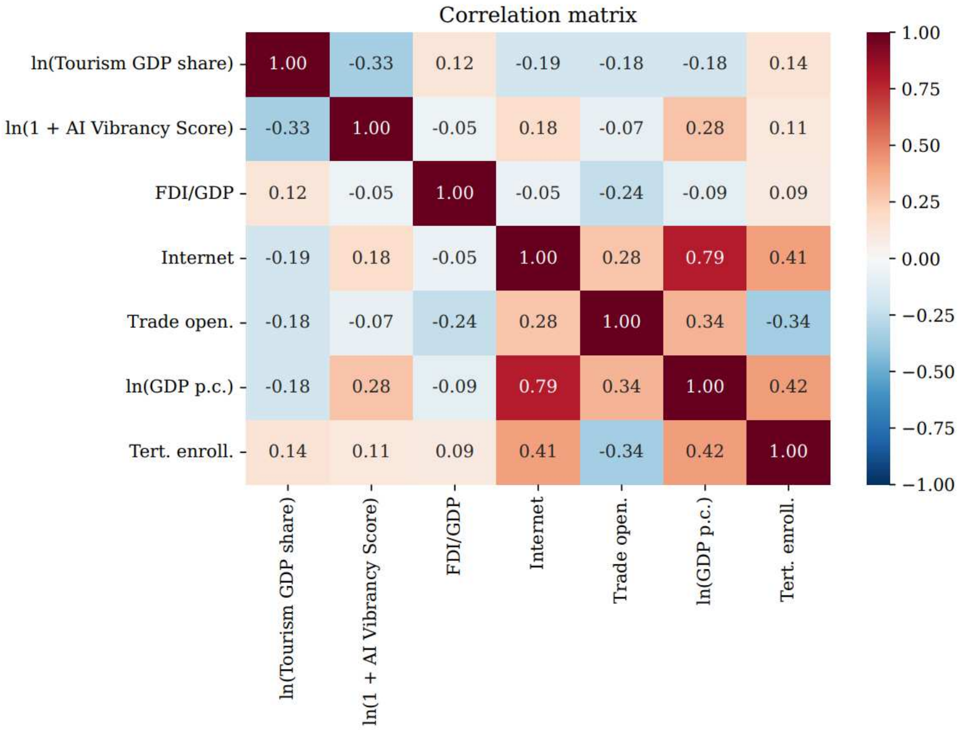


Figure B1. Correlation heatmap

APPENDIX C. Country fixed effects

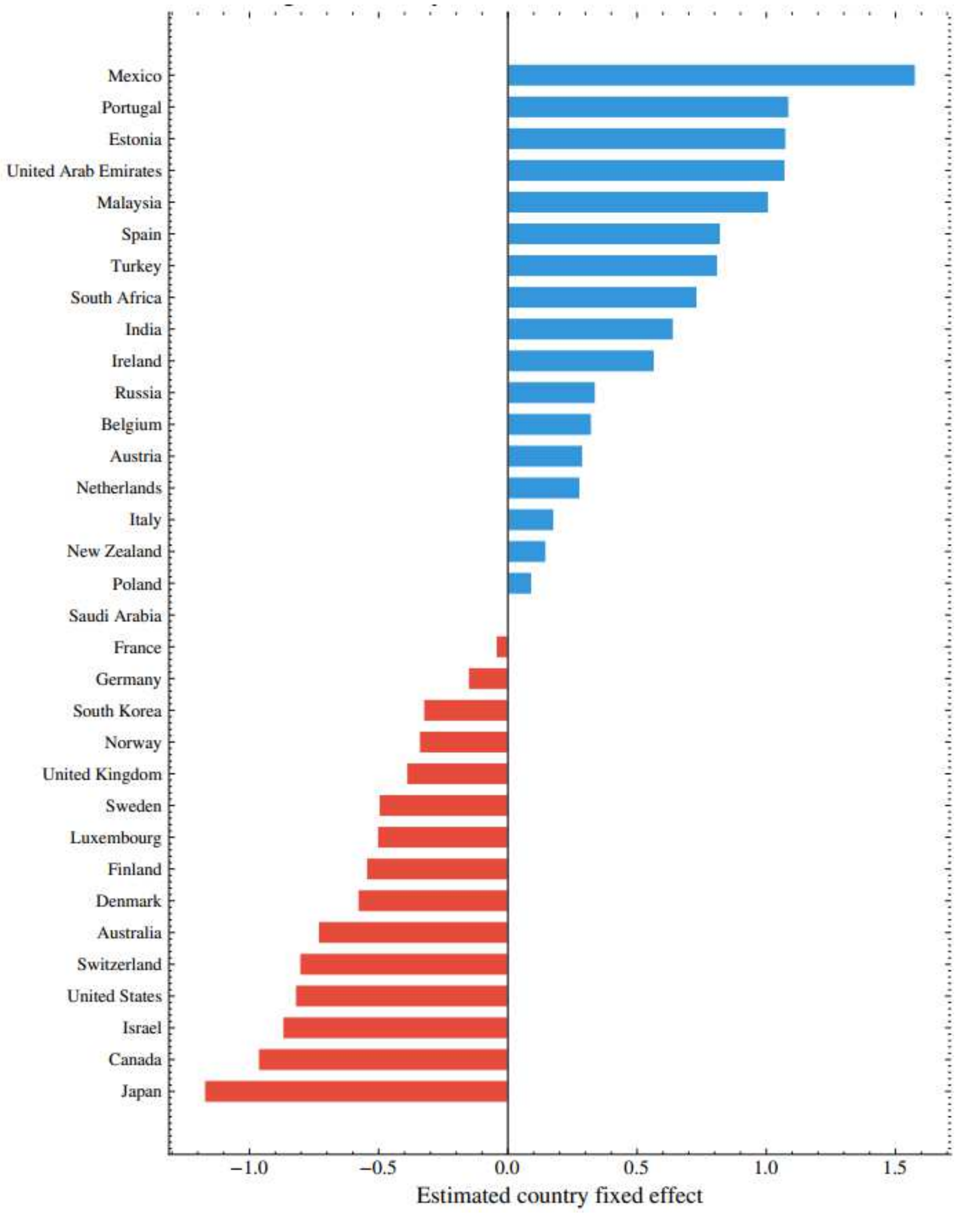
Table C1. Estimated country fixed effects on ln(Tourism GDP share), ranked by magnitude

Rank	Country	Income group	Tourism GDP mean, %	Fixed effect	Obs
1	Mexico	Upper middle	8.08	1.062	6
2	Portugal	High	7.37	0.946	7
3	Spain	High	6.13	0.782	5
4	Italy	High	5.61	0.699	2
5	Estonia	High	5.40	0.662	1
6	United Arab Emirates	High	5.40	0.640	3
7	Ireland	High	4.76	0.537	1
8	New Zealand	High	4.69	0.488	7
9	Austria	High	4.14	0.354	4
10	Turkey	Upper middle	3.78	0.282	4
11	Norway	High	3.48	0.205	5
12	Malaysia	Upper middle	4.23	0.194	7
13	France	High	3.33	0.171	4
14	Netherlands	High	3.54	0.163	5
15	Germany	High	3.26	0.123	5
16	United Kingdom	High	3.02	0.043	4
17	Belgium	High	3.00	0.042	4
18	United States	High	2.80	−0.001	6
19	South Africa	Upper middle	2.83	−0.007	6
20	Saudi Arabia	High	2.91	−0.080	6
21	South Korea	High	2.50	−0.108	1
22	Russia	Upper middle	2.40	−0.149	7
23	Australia	High	2.46	−0.161	7
24	Sweden	High	2.25	−0.227	5
25	Poland	High	2.20	−0.237	3
26	Finland	High	2.13	−0.305	6
27	Switzerland	High	2.05	−0.320	7

Table C1 (cont.). Estimated country fixed effects on ln(Tourism GDP share), ranked by magnitude

Rank	Country	Income group	Tourism GDP mean, %	Fixed effect	Obs
28	Denmark	High	1.95	−0.374	6
29	India	Lower middle	2.03	−0.440	6
30	Israel	High	1.90	−0.479	7
31	Canada	High	1.57	−0.614	7
32	Japan	High	1.42	−0.778	6
33	Luxembourg	High	1.01	−1.050	6

Note: Fixed effects represent demeaned country-level intercepts from the FE regression (Equation 1). Positive values indicate higher baseline tourism dependency after controlling for all observables; negative values indicate lower baseline dependency. Tourism GDP mean is the raw (untransformed) average over the sample period. The corresponding visual representation is presented in Figure C1 below.



Note: This figure presents the estimated country fixed effects from the preferred FE specification (M2). Positive (negative) values indicate that the country's tourism GDP share is above (below) the panel average, after controlling for AI Vibrancy, macroeconomic variables, and the COVID-19 dummy. See Table C1 for numerical values.

Figure C1. Country fixed effects on ln(Tourism GDP share)

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APPENDIX D. Robustness: aggregate AI Vibrancy Score

Table D1. Summary of the AI Vibrancy coefficient across all specifications

Specification	β (AI Vibrancy)	SE	p-value	N	R^2 within
M1: FE baseline (no controls)	–0.303**	0.093	0.003	163	0.735
M2: FE + controls (CRV1)	0.061	0.121	0.622	163	0.870
M3: TWFE	0.225	0.145	0.130	163	0.878
FE + controls (HC1)	0.061	0.134	> 0.10	163	0.870
y in levels (not log)	0.215	0.340	> 0.10	163	–
x in levels (not log1p)	–0.006	0.012	> 0.10	163	0.870
No COVID dummy	0.063	–	> 0.10	163	–
No ln(GDP p.c.)	0.054	–	> 0.10	163	–
Dynamic FE (y_{t-1} included)	–0.082	0.163	> 0.10	132	0.895
Excluding 2020–2021	–	–	> 0.10	111	–
Alt. DV: Tourism employment (OECD)	–0.036	0.134	0.790	131	0.922
Alt. DV: Tourism GVA (OECD)	–0.098	0.072	0.180	126	0.962

Note: All specifications include country fixed effects unless noted. Standard errors clustered by country (CRV1) except where indicated. The aggregate AI Vibrancy coefficient is statistically insignificant ($p > 0.10$) across all specifications except M1 (baseline without controls), where the significant negative effect ($\beta = -0.303$, $p = 0.003$) is attributable to omitted variable bias. "–" indicates values not extracted from the output; these specifications also yield insignificant AI coefficients. Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

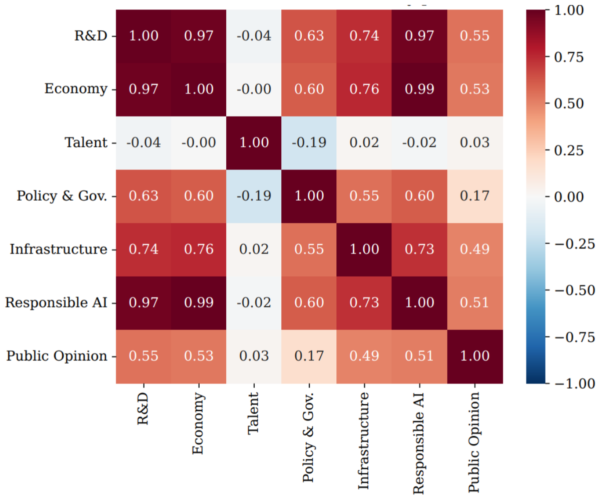
APPENDIX E. Variable definitions and data sources

Table E1. Variable definitions and data sources

Variable	Notation	Definition	Source
Tourism GDP share	y	Tourism direct GDP contribution, % of total GDP	UNWTO
AI Vibrancy Score	x	Composite AI Vibrancy Index (log1p-transformed)	Stanford HAI
R&D pillar	P_1	AI research & development intensity (YJ-transformed)	Stanford HAI
Economy pillar	P_2	AI commercial activity (YJ-transformed)	Stanford HAI
Talent pillar	P_3	AI human capital & education (YJ-transformed)	Stanford HAI
Policy & Governance	P_4	Government AI engagement (YJ-transformed)	Stanford HAI
Infrastructure pillar	P_5	AI-related infrastructure (YJ-transformed)	Stanford HAI
Responsible AI	P_6	Ethical AI frameworks (YJ-transformed; from 2019)	Stanford HAI
Public Opinion	P_6	Public attitudes toward AI (YJ-transformed; from 2021)	Stanford HAI
FDI, % of GDP	Z_1	Net foreign direct investment inflows, % of GDP	World Bank WDI
Internet users	Z_2	Individuals using the Internet, % of population	World Bank WDI
Trade openness	Z_3	Exports + imports, % of GDP	World Bank WDI
GDP per capita	Z_4	GDP per capita, constant 2015 US$ (log-transformed)	World Bank WDI
Tertiary enrollment	Z_5	Gross tertiary education enrollment rate, %	World Bank WDI
COVID dummy	D	Binary indicator: 1 for 2020–2021, 0 otherwise	Constructed
Tourism employment	y^{empl}	Tourism share of total employment, %	OECD TSA
Tourism GVA	y^{gva}	Tourism share of gross value added, %	OECD TSA

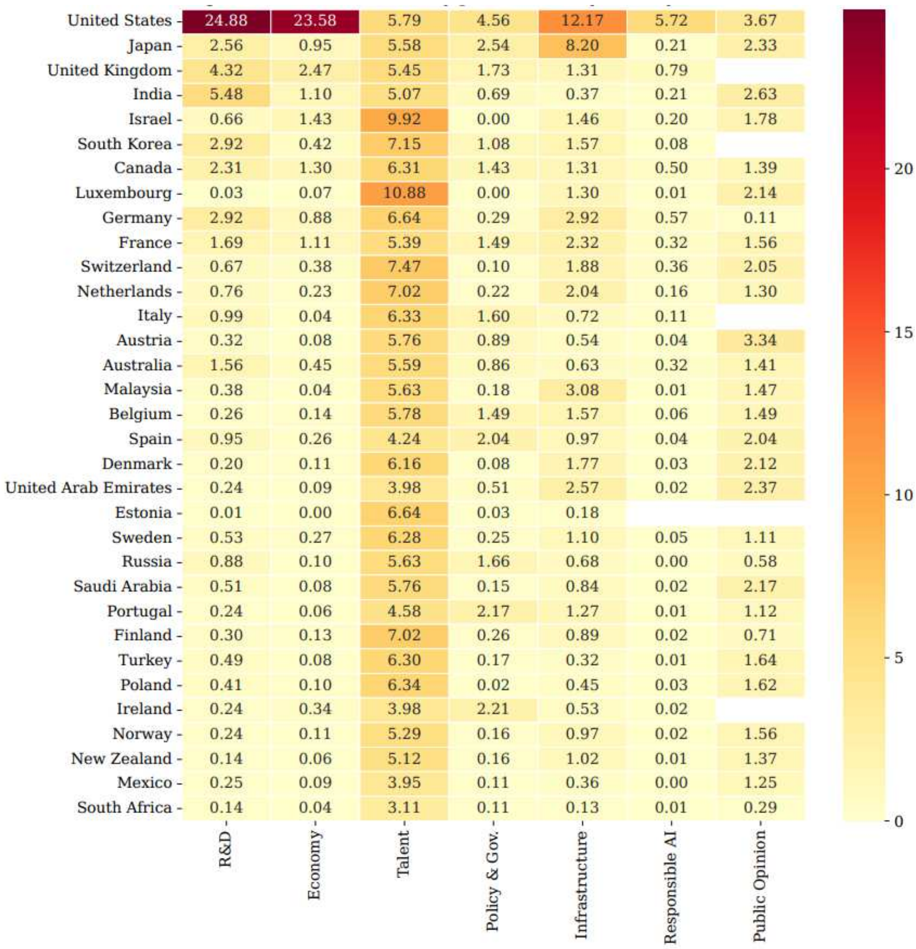
Note: YJ = Yeo-Johnson transformation. log1p = log(1 + x). Stanford HAI = Stanford University Human-Centered AI Institute.

APPENDIX F. Supplementary figures



Note: Pairwise Pearson correlations between the seven AI Vibrancy pillars (Yeo–Johnson transformed). The R&D–Economy (r = 0.97) and R&D–Responsible AI (r = 0.97) correlations indicate near-perfect collinearity, motivating the preferred five-pillar specification that excludes Responsible AI and Public Opinion.

Figure F1. Correlation between AI Vibrancy pillars



Note: Mean raw pillar values by country over the sample period. The United States dominates R&D, Economy, and Infrastructure; Israel and Luxembourg lead in Talent; and Policy and Governance is more evenly distributed across countries.

Figure F2. Mean AI Vibrancy pillar scores by country (2017–2023)

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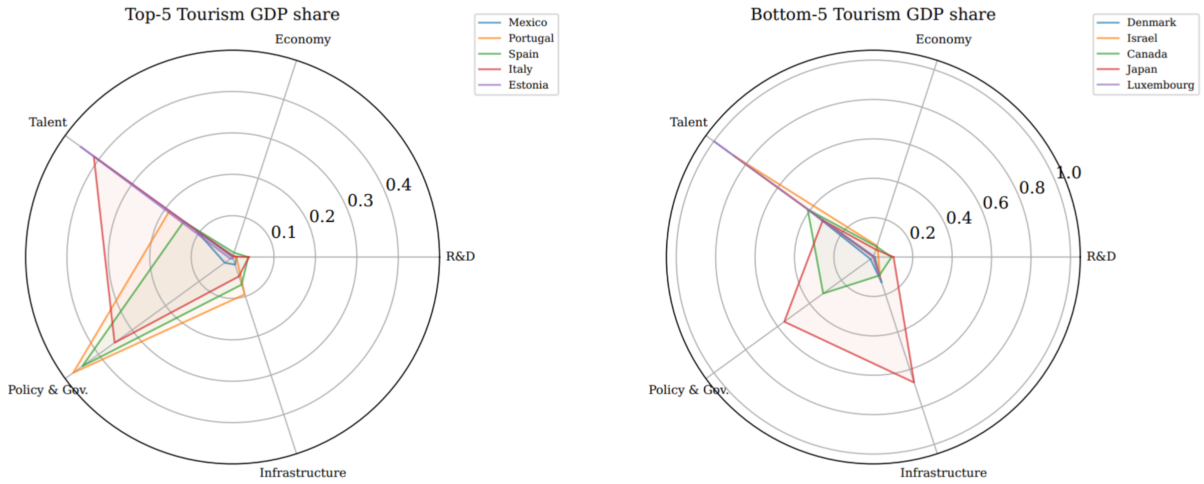
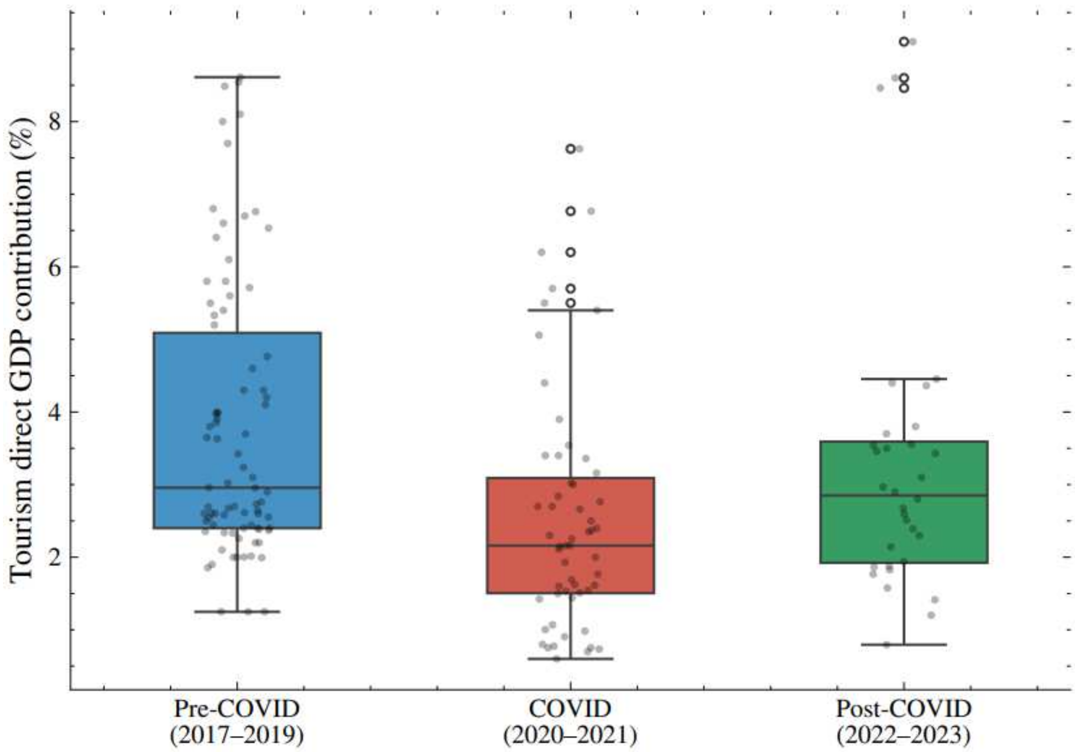


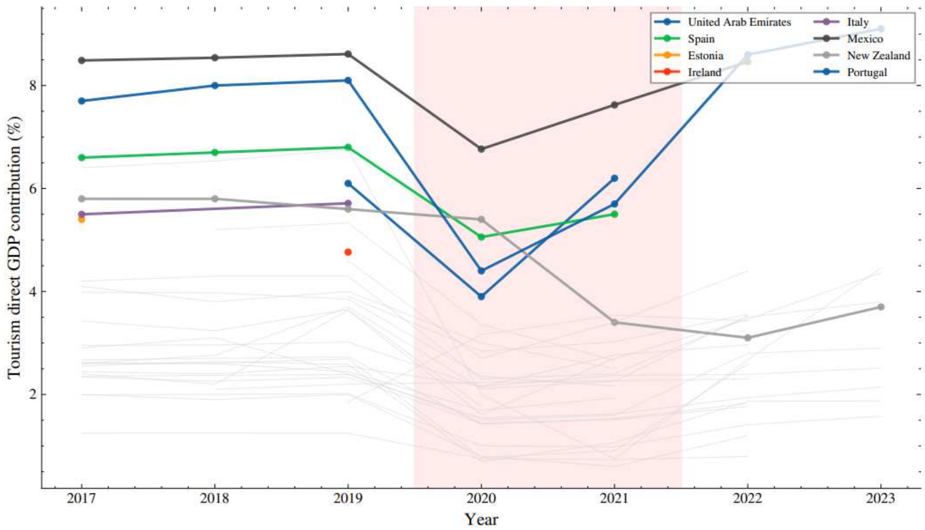
Note: Radar chart comparing the mean AI pillar profiles of the five countries with the highest tourism GDP share against the five countries with the lowest share. Countries with higher tourism dependence tend to have lower AI vibrancy across most pillars.

Figure F3. AI Vibrancy pillar profiles: top-5 vs bottom-5 tourism GDP share countries



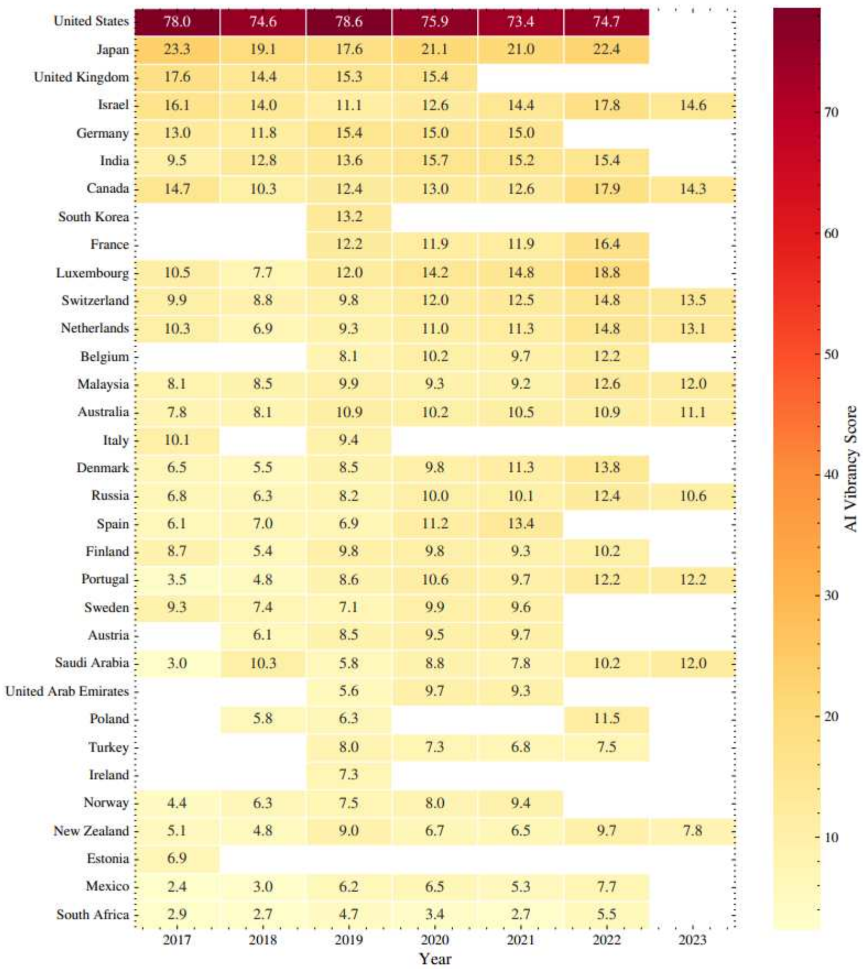
Note: Box plot comparing the distribution of tourism GDP share (%) across three periods: pre-COVID (2017–2019), COVID (2020–2021), and post-COVID (2022–2023). The median tourism GDP share declined from approximately 3.3% pre-pandemic to 2.0% during 2020–2021, recovering to approximately 3.0% in 2022–2023.

Figure F4. Tourism GDP share distribution by COVID period



Note: Spaghetti plot showing individual country trajectories of tourism GDP share over the sample period. The COVID-19 shock (2020–2021) is visible as a sharp decline across virtually all countries, with heterogeneous recovery patterns thereafter. Tourism-dependent economies (e.g., Mexico, Portugal, Spain) exhibit the largest absolute declines.

Figure F5. Country-level tourism GDP share trajectories (2017–2023)



Note: Heatmap displaying the composite AI Vibrancy Score for each country–year observation. The United States consistently dominates (scores above 70), while most countries cluster below 20. Missing cells reflect data unavailability in the Stanford HAI database.

Figure F6. AI Vibrancy Score by country and year (2017–2023)

http://dx.doi.org/10.21511/kpm.10(2).2026.06