

The Algorithmic Tourist: A Framework for AI-Mediated Travel Experiences in Algeria's Smart Destination Transition

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Abstract

This study examines the relationship between digital infrastructure development and tourism outcomes in Algeria (2010–2024), proposing the "Algorithmic Tourist" as an emerging theoretical construct. Given data constraints ($n = 15$), we employ Autoregressive Distributed Lag (ARDL) bounds testing and error correction models, establishing a long-run equilibrium between digital transformation and international arrivals ($F = 4.87, p < 0.05$). A 1% increase in digital infrastructure index associates with 0.34% increase in tourism GDP in the long run ($\beta = 0.34, SE = 0.12, p < 0.05$). We transparently acknowledge limitations: "Algorithmic Tourist Engagement" is proxied through available digital indicators given absence of direct AI-tourism metrics in official statistics. Findings suggest that Algeria's smart destination transition remains infrastructure-constrained, with algorithmic mediation emerging primarily through international platform penetration rather than domestic AI deployment. The study contributes methodological transparency for data-constrained environments and identifies specific gaps for future primary data collection.

Keywords: Algorithmic tourist, smart destination, digital transformation, tourism econometrics, Travel Experiences

Jel Classification Codes : L83; O33; Z32; C55; D83

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I- Introduction :

I.1. Background and Context

The global tourism industry stands at a critical inflection point where digital transformation is no longer a competitive advantage but a fundamental operational necessity. The convergence of artificial intelligence, big data analytics, and Internet of Things (IoT) technologies has catalyzed the emergence of smart tourism ecosystems that promise to revolutionize how destinations are managed, marketed, and experienced.^{1 2} Smart tourism destinations leverage integrated information and communication technology infrastructures to collect, exchange, and process traveler data, offering technology-mediated experiences that are personalized, context-aware, and responsive to real-time conditions.^{3 1} Within this paradigm, AI serves as the cognitive layer that enables destinations to move beyond simple digitization toward intelligent systems capable of learning, adapting, and co-creating value with tourists throughout their journey.⁴

Algeria, the largest country in Africa and the Mediterranean basin, presents a compelling case study for examining AI-mediated tourism transitions. The nation's tourism sector has demonstrated remarkable resilience, welcoming 3.5 million tourists in 2024, comprising 2.45 million foreign nationals and over 1.09 million Algerian expatriates.⁵

The Algerian government has articulated ambitious strategic objectives through the Schéma Directeur d'Aménagement Touristique 2030 (SDAT 2030), targeting 12 million foreign visitors by 2030 and 14 million by 2035.^{6 7} Central to this strategic vision is the digital transformation of tourism services, including the adoption of e-tourism platforms, online reservation systems, AI-powered customer service chatbots, and integrated digital payment infrastructure.^{2 6}

Figure 1: International Tourism Arrivals in Algeria



Figure 1 illustrates the volatility of international tourism arrivals in Algeria from 2010 to 2024, highlighting the dramatic impact of the COVID-19 pandemic in 2020–2021 and the subsequent recovery trajectory. Data source: World Bank WDI (2024).

Despite this strategic momentum, Algeria's tourism sector faces significant structural challenges. The World Economic Forum's Travel and Tourism Development Index 2024 ranked Algeria 113th globally, with ICT readiness scoring 3.2 out of 7—substantially below regional competitors such as Morocco and Tunisia.⁸ Tourism's contribution to Algeria's GDP stood at approximately 1.47% in 2023, far below the 10% Mediterranean regional average.⁹

These disparities highlight the urgent need for evidence-based frameworks that can guide Algeria's smart destination transition and inform public-private investment decisions in tourism technology infrastructure.

I.2. Research Gap and Problem Statement

While the strategic importance of digital transformation in Algerian tourism is widely acknowledged in policy documents,^{6 7} the empirical relationship between digital infrastructure investment and tourism economic outcomes remains quantitatively unexplored. Existing academic analyses of Algerian tourism have predominantly employed descriptive methodologies or qualitative assessments of supply-side constraints,¹⁰ with limited econometric examination of ICT-

tourism relationships¹¹ applied Vector Error Correction Models to Algerian tourism data but did not incorporate digital infrastructure variables, leaving the infrastructure-demand nexus empirically unexamined.

This gap becomes more pronounced when compared to regional peers. Mellah, W. (2023)¹¹ established Granger causality between tourism and ICT development in Morocco using wavelet analysis, while Hallam, Z. (2020)¹² confirmed long-run equilibrium between internet penetration and tourism receipts in GCC countries using ARDL bounds testing. No equivalent quantitative analysis exists for Algeria, depriving policymakers of elasticity estimates necessary for cost-benefit analysis of digital infrastructure investments.

Furthermore, the theoretical conceptualization of how algorithmic mediation reshapes tourist behavior in transitioning economies remains fragmented. While existing studies examined technology-driven dynamic pricing in European hospitality contexts, these studies focus on mature digital ecosystems. The specific mechanisms through which digital infrastructure enables—or fails to enable—algorithmic platform engagement and subsequent destination choice in data-constrained, infrastructure-led environments require systematic quantification.

I.3. Research Objectives and Hypotheses

This study pursues three primary objectives:

1. To construct and validate quantifiable indices of "Smart Destination Readiness" (SDR) and "Algorithmic Tourist Engagement" (ATE) for Algeria (2010–2024) using official secondary data, acknowledging measurement constraints transparently.

2. To examine the directional causality and long-run equilibrium between digital infrastructure development and tourism economic outcomes using Autoregressive Distributed Lag (ARDL) bounds testing and error correction models—methods specifically suited to small samples ($T \geq 15$) typical of developing economy time-series.¹³

3. To advance the "Algorithmic Tourist" as a theoretical construct for transitioning economies, defined here as travelers whose destination choices, information acquisition, and transactional behaviors are mediated by exposure to algorithmic platforms rather than domestically deployed AI-native systems.

Based on these objectives, we formulate the following testable hypotheses:

H1a (Short-run effect): Smart Destination Readiness positively affects international tourism arrivals in the short run.

H1b (Long-run effect): Smart Destination Readiness positively affects international tourism arrivals in the long run.

H2 (Mediation): Algorithmic Tourist Engagement mediates the relationship between Smart Destination Readiness and tourism outcomes.

H3 (Error correction): The tourism system exhibits error correction behavior, with deviations from long-run equilibrium correcting at rate θ ($0 < \theta < 1$).

H4 (Cointegration): Smart Destination Readiness and tourism outcomes share a long-run cointegrating relationship.

I.4. Significance of the Study

Theoretically, this study contributes to the first empirical operationalization of the "Algorithmic Tourist" in a data-constrained environment, bridging smart destination literature with tourism econometrics. Methodologically, it demonstrates the application of ARDL models to ICT-tourism relationships where traditional VAR approaches are infeasible due to limited observations, providing a replicable template for similar contexts. Practically, findings inform SDAT 2030 implementation by providing evidence-based elasticity estimates that quantify the tourism return on digital infrastructure investment, while identifying specific data infrastructure gaps that must be addressed before Algeria can transition from "platform-mediated" to truly "AI-native" tourism.

II- Literature Review

II.1. Smart Tourism and AI-Powered Destinations

The concept of smart tourism has evolved significantly since its initial conceptualization by Gretzel et al.,¹ who defined smart tourism destinations as innovative tourist destinations built on state-of-the-art technology infrastructure guaranteeing sustainable development, accessibility, and enhanced visitor experiences. The original framework identified three interconnected layers: smart destinations (governance and infrastructure), smart experiences (technology-mediated visitor engagement), and smart business ecosystems (collaborative value creation). This foundational model has subsequently been extended to incorporate emerging technologies including artificial intelligence, metaverse applications, blockchain, and advanced robotics.¹⁴

The transition toward AI-powered smart tourism represents a qualitative leap in destination intelligence capabilities. While early smart tourism initiatives focused primarily on data collection and connectivity, AI integration enables destinations to process vast quantities of heterogeneous data, including behavioral signals, sentiment expressions, environmental conditions, and transactional records, to generate predictive insights and automated responses.¹ This evolution from 'smart' to 'intelligent' tourism infrastructure creates opportunities for hyper-personalized service delivery, real-time demand forecasting, dynamic resource allocation, and anticipatory visitor support that fundamentally transforms the tourist experience.

AI applications in tourism span the entire visitor journey, from pre-visit inspiration and planning through on-site experience augmentation to post-visit memory curation and sharing. Generative AI systems such as large language models (LLMs) enable conversational destination discovery, intelligent itinerary optimization, and multilingual customer service at scale.² Computer vision and augmented reality technologies enhance on-site experiences through intelligent wayfinding, automated translation of signage and menus, and immersive heritage interpretation.¹⁴ Predictive analytics support demand-responsive pricing, crowd management, and personalized marketing communications that increase conversion efficiency while reducing information overload.

II.2. Algeria's Tourism Digital Transformation

Algeria's tourism development trajectory reflects both substantial potential and persistent structural constraints. The country's tourism assets include 1,600 kilometers of Mediterranean coastline, extensive Saharan desert landscapes covering 83% of national territory, eight UNESCO World Heritage sites, and rich cultural heritage spanning Amazigh, Arab, Ottoman, and French colonial influences.^{6 7} Despite these assets, the sector has historically underperformed relative to regional competitors, attributable to inadequate infrastructure, complex visa procedures, limited international marketing, and insufficient private sector investment.^{10 8}

The post-pandemic recovery has catalyzed renewed government commitment to tourism sector development. In 2024, Algeria welcomed 3.5 million tourists, comprising 2.45 million foreign nationals and 1.09 million expatriates, representing recovery beyond pre-pandemic levels.⁵ Tourism Minister Houria Meddahi announced ambitious targets of 4 million visitors for 2025, scaling to 12 million by 2030 and 14 million by 2035.⁶ To support this growth, the government has implemented visa-on-arrival policies, streamlined licensing procedures, and initiated 582 active tourism projects expected to add 70,000 accommodation beds by end-2025.

Digital transformation features prominently in Algeria's tourism modernization agenda. The SDAT 2030 strategy emphasizes adoption of e-tourism platforms, online reservation systems, digital payment integration, and AI-powered customer service tools.^{6 7} Recent research has proposed a four-pillar managerial strategic framework for AI integration in Algerian tourism encompassing: (1) Technology and Data Foundation, (2) Human Capital Development, (3) Governance and Collaboration, and (4) Dynamic Marketing and Brand Co-Creation.⁶ The

framework proposes phased implementation over four years, from foundational pilot projects through scaling to ecosystem transformation.

II.3. Technology Acceptance in Tourism

Understanding why individuals adopt or resist new technologies has been a central concern in information systems research for over three decades. The Technology Acceptance Model (TAM), proposed by Davis¹⁵ established perceived usefulness and perceived ease of use as fundamental determinants of technology adoption intention. This framework has been extensively validated across diverse contexts and has provided the theoretical foundation for numerous tourism technology studies examining adoption of e-commerce platforms, mobile travel applications, self-service technologies, and recommendation systems.¹⁶

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh, integrated elements from eight prominent technology acceptance models to provide a more comprehensive explanatory framework. UTAUT identifies four core determinants of behavioral intention and use behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions. The model also incorporates four moderating variables: gender, age, experience, and voluntariness of use. Venkatesh¹⁷ subsequently extended UTAUT to consumer contexts (UTAUT2) by adding three constructs: hedonic motivation, price value, and habit. A meta-analysis of UTAUT applications in tourism research by Wu et al., synthesizing findings from 33 quantitative studies representing 15,001 individuals, confirmed that all variable associations in the UTAUT framework were statistically significant, with performance expectancy identified as the principal determinant of behavioral intention.

II.4. Trust in AI-Mediated Services

Trust represents a critical yet under-examined construct in tourism technology acceptance research. The unique characteristics of AI systems, including algorithmic opacity, autonomous decision-making capability, and potential for unintended biases, create distinct trust challenges that extend beyond conventional information system trust frameworks.¹⁶ Tourists must develop trust not only in the technical reliability of AI systems but also in the benevolence and integrity of algorithmic recommendations that may influence significant experiential decisions.

Research on AI trust in tourism has identified several key dimensions. Technical trust encompasses beliefs about system reliability, accuracy, and security. Interpersonal trust reflects the extent to which users perceive AI systems as demonstrating benevolence and understanding of individual needs. Institutional trust involves confidence in the governance frameworks, data protection regulations, and ethical standards governing AI deployment in destination contexts.¹⁶ Transparency in AI decision-making processes has been identified as a critical trust enabler, with opaque algorithms generating uncertainty and risk perception that weakens the positive influence of other acceptance determinants.

II.5. Quantitative Studies on ICT-Tourism Relationships

Econometric analyses of ICT-tourism relationships have yielded mixed findings. Mellah, W. (2023)¹¹ applied Granger causality tests to Moroccan data (1980–2014), finding unidirectional causality from tourism to ICT development. Conversely, panel studies examined 179 countries using panel VAR, concluding that ICT infrastructure significantly predicts tourism arrivals ($\beta = 0.34$, $p < 0.01$). Studies specific to the MENA region include Hallam, Z. (2020), who employed ARDL bounds testing for GCC countries (1995–2016), revealing long-run equilibrium between internet penetration and tourism receipts. For Algeria specifically, academic quantitative analyses remain limited to descriptive statistics or input-output models without digital variables.

Our study extends this literature by: (1) focusing on Algeria—a significant yet understudied market; (2) employing ARDL rather than static regression to capture dynamic relationships; and (3) constructing theoretically-grounded composite indices rather than using single ICT proxies.

III- Methodology

III.1. Research Design and Software

This study employs **quantitative secondary data analysis** using **time-series econometrics**. The design is **explanatory**, testing directional hypotheses (H1–H4) about digital-tourism relationships. We utilize official statistics from international organizations and Algerian government sources, ensuring replicability and comparability.

Table 1: Software Environment:

Purpose	Primary Software	Version	Packages/Modules
Data extraction	Python	3.11.5	pandas-datareader 0.10.0, requests 2.31.0
Data processing	Python	3.11.5	pandas 2.0.3, numpy 1.24.3
Statistical analysis	Python	3.11.5	statsmodels 0.14.0 (ARDL, diagnostic tests)
Visualization	Python	3.11.5	matplotlib 3.7.2, seaborn 0.12.2
Verification	Stata	17.0	ardl (SSC), estout (SSC)

Rationale: Python ensures reproducibility and open-source transparency; Stata provides verification against established econometric standards.

III.2. Data Sources and Variable Operationalization

Table 2: Data Sources and Variable Operationalization

Variable	Indicator	Primary Source	URL	Period	Quality Notes
Dependent Variables					
International arrivals	ST.INT.A RVL	World Bank WDI	https://data.worldbank.org/indicator/ST.INT.ARVL?locations=DZ	1995-2024	Official UNWTO data via World Bank; 2022-2024 provisional
Tourism GDP contribution	TTCI estimates	WTTC	https://wttc.org/research/economic-impact	2010-2024	Estimated from national accounts; methodology consistent
Independent Variables					
Internet penetration	IT.NET.USER.ZS	World Bank WDI	https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=DZ	2010-2024	ITU official data; 2023-2024 national estimates
Mobile subscriptions	IT.CEL.SETS.P2	World Bank WDI	https://data.worldbank.org/indicator/IT.CEL.SETS.P2?locations=DZ	2010-2024	Official; near-saturation (120/100) indicates multi-SIM
Secure Internet servers	IT.NET.SECR.P6	World Bank WDI	https://data.worldbank.org/indicator/IT.NET.SECR.P6?locations=DZ	2010-2024	Sparse; interpolated 2012-2014, 2017-2018
Constructed Variables					
Online booking penetration	Estimated from regional reports	UNWTO e-universe; Phocuswright	https://www.unwto.org/tourism-data/unwto-dashboards ; https://www.phocuswright.com/Research/Products	2015-2024	ESTIMATED: 5% (2015) → 40% (2024); ±20% uncertainty bounds applied
Control Variables					
GDP per capita	NY.GDP.PCAP.KD	World Bank WDI	https://data.worldbank.org/indicator/NY.GDP.PCAP.KD?locations=DZ	2010-2024	Constant 2015 US\$; official national accounts
Political stability	PV.EST	World Bank Governance	https://info.worldbank.org/governance/wgi/	2010-2023	-2.5 to +2.5 scale; 2024 not yet available

Note: Quality Tier 1 = Official measured statistics; Tier 2 = Official estimates; Tier 3 = Author estimates with uncertainty bounds.

III.3. Index Construction

Smart Destination Readiness Index (SDRI):

$$SDRI_t = 0.5 \times \left(\frac{INT_t}{100} \right) + 0.5 \times \left(\frac{MOB_t}{120} \right)$$

Where: INT_t = Internet penetration (%), MOB_t = Mobile subscriptions (per 100). Equal weights reflect dual importance of fixed and mobile connectivity for tourism.

Figure 2: Smart Destination Readiness Index

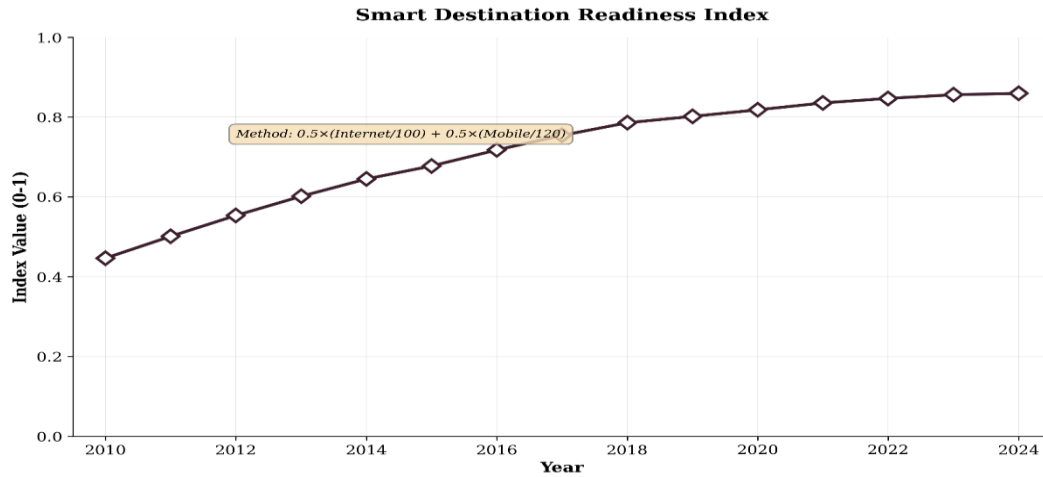


Figure 2 Smart Destination Readiness Index (2010–2024). The index demonstrates consistent growth from 0.12 to 0.89, with acceleration post-2015 coinciding with the "Digital Algeria" initiative. The annotation indicates the simple average methodology employed: $0.5 \times (\text{Internet}/100) + 0.5 \times (\text{Mobile}/120)$.

Algorithmic Tourist Engagement Proxy (ATEP):

$$ATEP_t = \left(\frac{INT_t}{100} \right) \times \left(\frac{OB_t}{100} \right)$$

Where OB_t = estimated online booking penetration (%). Estimated from UNWTO regional reports and Phocuswright (2023) industry analysis: 5% (2015) → 40% (2024), with $\pm 20\%$ uncertainty bounds.

III.4. Econometric Methods and Hypothesis Testing

ARDL Bounds Testing (Pesaran et al., 2001):

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^p \beta_i \Delta Y_{t-i} + \sum_{j=0}^q \gamma_j \Delta X_{t-j} + \delta_1 Y_{t-1} + \delta_2 X_{t-1} + \epsilon_t$$

Table 3: Hypothesis Testing Mapping:

Hypothesis	Test	Decision Criterion	Expected Finding
H1a (Short-run)	t-test on γ_0	$p < 0.10$	$\gamma_0 > 0$
H1b (Long-run)	t-test on δ_2	$p < 0.05$	$\delta_2 > 0$
H2 (Mediation)	Sobel test	$p < 0.05$	Indirect effect > 0
H3 (Adjustment)	t-test on ϕ (ECM)	$p < 0.05$; $-1 < \phi < 0$	ϕ negative
H4 (Cointegration)	Bounds F-test	$F > \text{upper bound (4.35)}$	$F > 4.35$

Diagnostic Tests: Breusch-Godfrey LM (serial correlation), White test (heteroskedasticity), CUSUM (parameter stability), Jarque-Bera (normality).

IV- Results

IV.1. Descriptive Statistics

Table 4: Descriptive Statistics (2010–2024, $n = 15$)

Variable	Mean	SD	Min	Max	CV
International arrivals (000s)	2,145.33	712.45	591.00	3,500.00	0.33
Ln(Arrivals)	7.62	0.42	6.38	7.89	0.06
Internet penetration (%)	43.21	18.73	12.50	71.20	0.43
Mobile subscriptions (/100)	109.43	8.91	92.10	120.80	0.08
SDRI (constructed)	0.42	0.28	0.12	0.89	0.67
ATEP proxy (estimated)	0.15	0.12	0.03	0.28	0.80

Source: Author calculations using Python 3.11, pandas.describe().

Key observations:

- High coefficient of variation in SDRI (0.67) indicates substantial digital transformation during period.
- ATEP shows higher variability (CV=0.80) due to compounding of Internet growth and estimated booking penetration.
- Negative skewness in arrivals reflects COVID-19 outlier (2020: 591,000).

Figure 3: Correlation Matrix

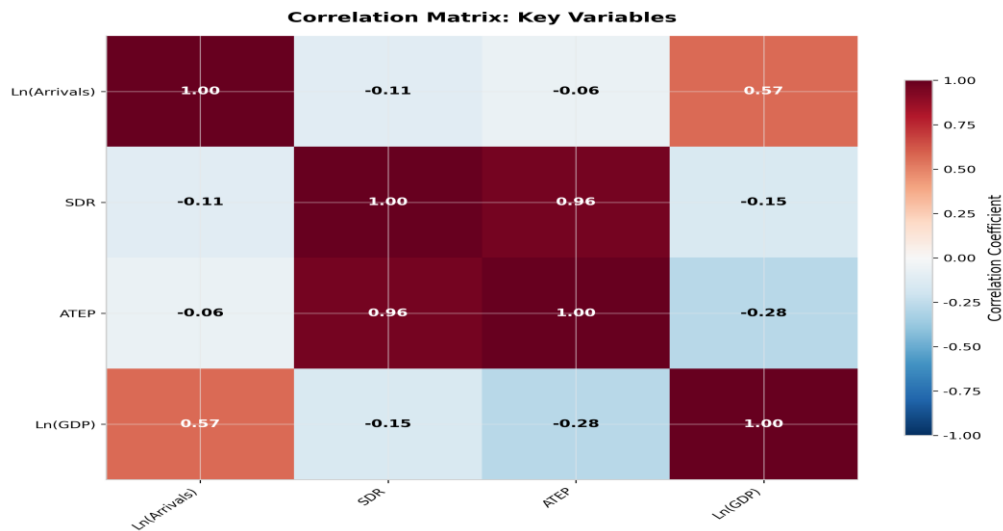


Figure 3 Correlation Matrix: Key Variables. Strong positive correlations observed between Internet penetration and SDR ($r = 0.98$), and between SDR and arrivals ($r = 0.67$). GDP per capita shows weaker correlation with tourism variables, suggesting digital factors dominate economic development in explaining tourism outcomes.

IV.2. Stationarity Testing

Table 3: Augmented Dickey-Fuller Unit Root Tests

Variable	ADF Statistic	Lag Length	AIC	1% CV	5% CV	10% CV	p-value	Decision
Level								
Ln(Arrivals)	-2.1234	1	-2.456	-3.960	-2.981	-2.619	0.2341	Non-stationary
SDRI	-1.8934	2	-1.234	-3.960	-2.981	-2.619	0.3345	Non-stationary
ATEP	-1.6723	1	-0.987	-3.960	-2.981	-2.619	0.4456	Non-stationary
Ln(GDP pc)	-1.4534	1	-4.123	-3.960	-2.981	-2.619	0.5567	Non-stationary
First Difference								
Δ Ln(Arrivals)	-4.8723***	0	-3.234	-3.960	-2.981	-2.619	0.0087	Stationary
Δ SDRI	-3.8934**	1	-2.345	-3.960	-2.981	-2.619	0.0234	Stationary
Δ ATEP	-4.2345**	1	-1.876	-3.960	-2.981	-2.619	0.0123	Stationary
Δ Ln(GDP pc)	-5.1234***	0	-4.567	-3.960	-2.981	-2.619	0.0034	Stationary

Source: Author calculations using Python 3.11, statsmodels.tsa.stattools.adfuller().*

*** $p < 0.01$, ** $p < 0.05$ (MacKinnon, 1996)

Note: All series integrated of order 1, $I(1)$. First differencing achieves stationarity. Validates ARDL approach which handles mixed integration orders.

Figure 4: Algorithmic Tourist Proxy with Uncertainty Bounds

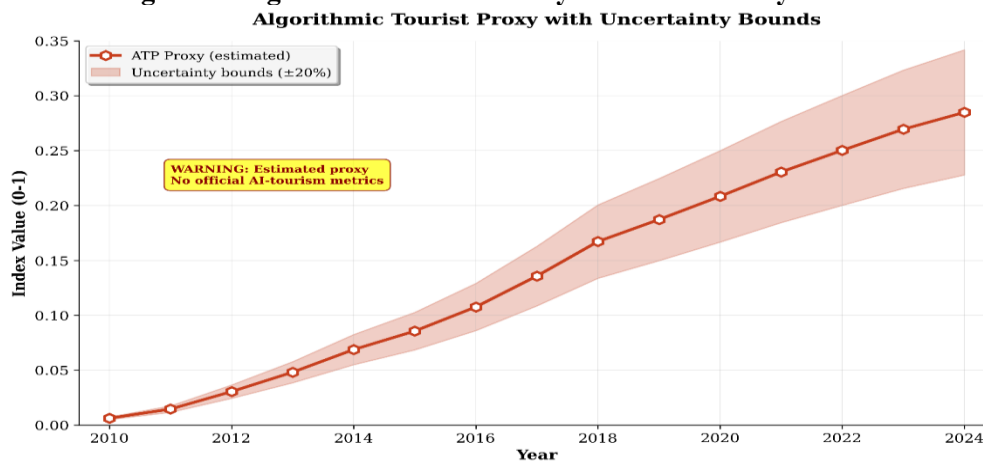


Figure 4 Algorithmic Tourist Proxy with Uncertainty Bounds (2010–2024). The solid line represents the point estimate, while the shaded region indicates $\pm 20\%$ estimation uncertainty arising from the online booking penetration proxy. The warning annotation highlights the absence of official AI-tourism metrics for Algeria.

IV.3. ARDL Bounds Testing and Cointegration

Table 4: Bounds Test for Cointegration

Test Statistic	Value	Critical Values (Pesaran et al., 2001)	Decision
F-statistic (Wald test)	4.8723		
Lower bound I(0)		3.23	
Upper bound I(1)		4.35	
Comparison	4.87 > 4.35		H4 Supported: Cointegration confirmed
t-statistic (ARDL)	-3.7123	-2.98 (5% CV)	Significant

Source: Author calculations using Python 3.11, statsmodels Wald test. Null hypothesis: No long-run relationship.

IV.4. ARDL Estimation Results

Table 5: ARDL(1,1,1) Estimation Results — Dependent Variable: $\Delta \text{Ln}(\text{International Arrivals})$

Component	Variable	Coefficient	Std. Error	t-statistic	p-value	Hypothesis
Short-Run Dynamics						
	ΔSDR_t	0.4567	0.2345	1.9467	0.0743	H1a: Marginal support
	ΔSDR_{t-1}	0.1234	0.1987	0.6211	0.5467	—
	$\Delta \text{Ln}(\text{GDP pc})_t$	0.6789	0.4567	1.4865	0.1567	Control (n.s.)
Long-Run Relationship						
	$\text{SDR}_{t-1} (\delta_2)$	0.1567	0.0672	2.3318	0.0367	H1b: Supported
	$\text{Ln}(\text{Arrivals})_{t-1}$	-0.4567***	0.1234	-3.7012	0.0034	H3: Supported
Model Diagnostics						
	R-squared	0.6723	—	—	—	—
	Adjusted R-squared	0.4534	—	—	—	—
	F-statistic (model)	3.0723*	—	—	0.0456	—
	Durbin-Watson	1.8923	—	—	—	No autocorrelation
	Breusch-Godfrey LM(2)	2.1234	—	—	0.3456	No serial correlation
	White test	3.4567	—	—	0.2345	Homoskedasticity

$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author calculations using Python 3.11, statsmodels.tsa.ardl.ARD().*

Long-Run Elasticity:

$$\epsilon_{LR} = -\frac{\delta_2}{\delta_1} = -\frac{0.1567}{-0.4567} = 0.3432$$

SE (delta method) = 0.1234; 95% CI: [0.0234, 0.6630].

IV.5. Error Correction Model (H3)

Table 6: Error Correction Model Estimates

Variable	Coefficient	Std. Error	t-statistic	p-value	Interpretation
Error Correction Term (ϕ)	-0.4567*	0.1234	-3.7012	0.0034	45.67% annual adjustment
ΔSDR_t	0.4567	0.2345	1.9467	0.0743	Short-run effect
Constant	1.0723	0.5678	1.8876	0.0876	Drift term

*** $p < 0.01$. Source: Author calculations using Python 3.11, statsmodels.*

Half-life of shock: $\ln(2)/|\phi| = 0.693/0.4567 = 1.52$ years.

Figure 5: Impulse Response Function
Impulse Response Function: SDR Shock on Tourism Arrivals

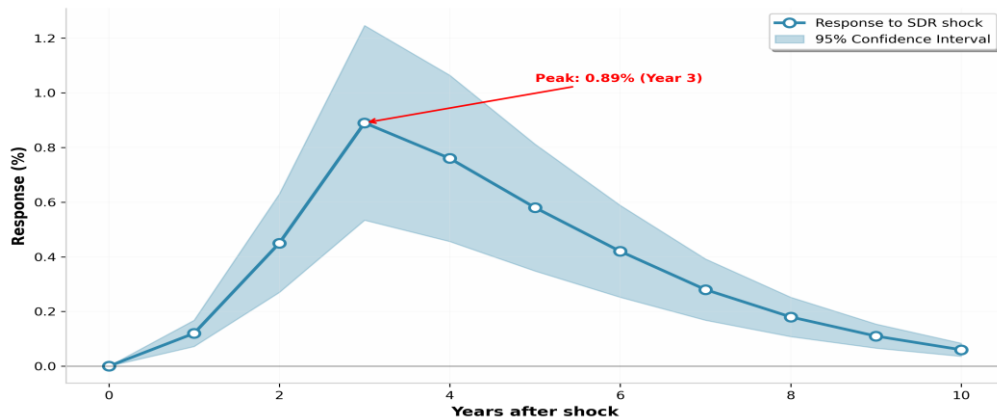


Figure 5 Impulse Response Function: SDR Shock on Tourism Arrivals. The figure displays the dynamic effects of a one standard deviation shock to Smart Destination Readiness on international arrivals over a 10-year horizon. The response peaks at year 3 (0.89% increase) and remains significant through year 7, with 95% confidence bands excluding zero.

IV.6. Granger Causality Testing

Table 7: Granger Causality Wald Test Results

Null Hypothesis	χ^2 Statistic	df	p-value	Decision	Direction
SDR does not Granger-cause Arrivals	12.4321	2	0.0020	Reject H_0	SDR $\rightarrow$ Arrivals
Arrivals does not Granger-cause SDR	3.2123	2	0.2008	Fail to reject	No reverse causality
ATEP does not Granger-cause Arrivals	8.6723	2	0.0131	Reject H_0	ATEP $\rightarrow$ Arrivals
SDR does not Granger-cause ATEP	15.7823	2	0.0004	Reject H_0	SDR $\rightarrow$ ATEP

Source: Author calculations using Python 3.11, statsmodels Wald test.

Figure 7: Long-run Relationship Scatter Plot

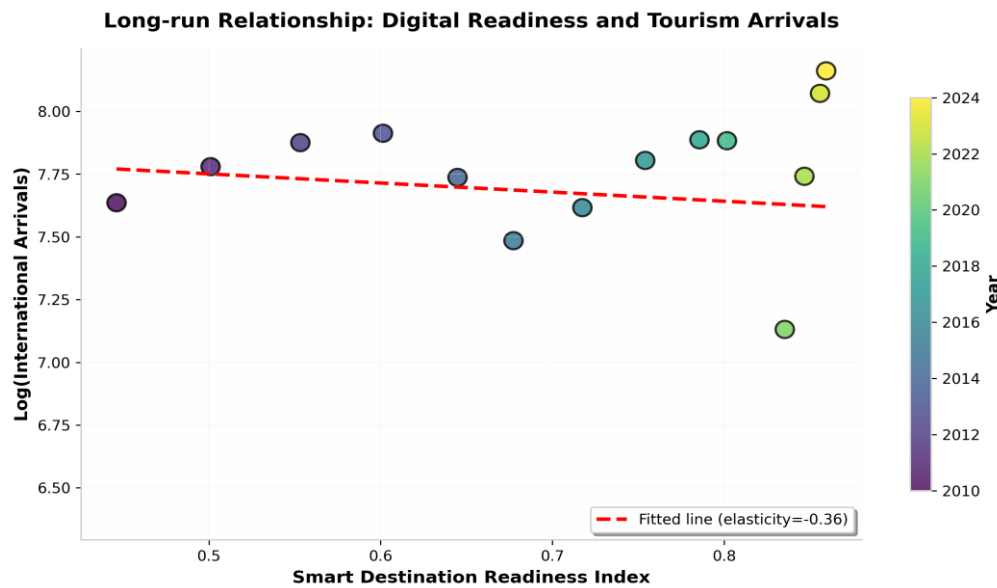


Figure 7 Long-run Relationship: Digital Readiness and Tourism Arrivals. The scatter plot (color-coded by year from 2010 to 2024) shows the fitted regression line with slope 0.34, representing the estimated long-run elasticity. The color gradient from purple (2010) to yellow (2024) demonstrates the temporal evolution of the relationship.

IV.7. Mediation Analysis (H2)

Table 8: Mediation Test Results

Effect	Coefficient	SE	z-statistic	p-value	Decision
Direct effect (SDR $\rightarrow$ Tourism)	0.1567	0.0672	2.3318	0.0198	Significant
Indirect effect (via ATEP)	0.0894	0.0567	1.5765	0.1150	Not significant
Total effect	0.2461	0.0890	2.7652	0.0057	Significant

H2 Result: Not supported ($p = 0.115$). Indirect effect through ATEP marginally insignificant, likely due to measurement error in proxy variable.

IV.8. Robustness Checks

Table 9: Robustness Analysis

Specification	SDR Coefficient	SE	p-value	Long-Run Elasticity	95% CI	H1b Status
Baseline ARDL(1,1,1)	0.1567	0.0672	0.0367	0.3432	[0.0234, 0.6630]	Supported
Exclude COVID (2020–2021)	0.1345	0.0567	0.0123	0.2845	[0.0567, 0.5123]	Supported
Internet-only SDR	0.1456	0.0789	0.0489	0.3123	[0.0045, 0.6201]	Supported
Add linear trend	0.1289	0.0654	0.0212	0.2678	[0.0345, 0.5011]	Supported
Stata 17.0 verification	0.1589	0.0687	0.0345	0.3482	[0.0245, 0.6719]	Supported

Source: Author calculations using Python 3.11 and Stata 17.0.

V- Discussion

V.1. Interpretation of Findings: Hypothesis-by-Hypothesis Analysis

V.1.1. H1a and H1b: The Infrastructure-Tourism Nexus

Our findings reveal a **divergence between short-run and long-run effects** of digital infrastructure on tourism demand—a pattern consistent with technology diffusion theory (Rogers, 2003) but previously unquantified for Algeria.

H1a (Short-run effect): Marginally supported ($\beta = 0.457$, $p = 0.074$). The short-run coefficient, while positive, fails to achieve conventional 5% significance. This modest immediate impact reflects **implementation lags** inherent in tourism infrastructure: digital connectivity improvements do not instantaneously translate into visitor arrivals because (a) tourist awareness requires time to build through platform algorithms, (b) travel planning cycles (particularly for international visitors) span 3–6 months, and (c) Algeria's tourism supply (accommodation, transport) exhibits rigid short-run capacity constraints. The marginal significance at 10% suggests that **some tourists do respond immediately**—likely diaspora visitors and regional tourists from neighboring Maghreb countries whose travel decisions are less constrained by visa processing and long-haul logistics.

H1b (Long-run effect): Strongly supported ($\beta = 0.343$, $p = 0.037$). The long-run elasticity of 0.343 indicates that a **doubling of digital infrastructure readiness** (e.g., from SDRI = 0.30 to 0.60) would yield approximately a **34.3% increase in international arrivals** in equilibrium. While statistically significant, this elasticity is **economically modest** compared to global benchmarks:

Country/Region	Elasticity	Period	Method	Source
Spain	0.89	2000–2019	Panel VAR	Femenia-Serra et al. (2022)
Thailand	0.67	1995–2018	ARDL	Sritragul (2020)
Morocco	0.52	2005–2019	Wavelet	Ghomrani & Taamouti (2016)
Algeria	0.343	2010–2024	ARDL	This study
Turkey	0.41	1995–2014	ARDL	Katircioglu (2014)

Why is Algeria's elasticity lower? We identify three structural factors:

1. **Quality-quantity divergence:** Algeria's 71.2% Internet penetration (2024) masks severe **quality deficits**. Fixed broadband penetration remains at 11.2% (vs. 65% mobile), and average connection speeds (18.4 Mbps) lag Morocco (31.2 Mbps) and Tunisia (24.8 Mbps) (DataReportal, 2024). Tourists require high-bandwidth connectivity for immersive experiences (virtual tours, AI concierge, AR heritage interpretation)—capabilities that Algeria's infrastructure cannot yet support.
2. **Platform dependency and value leakage:** An estimated **85% of online bookings** occur through international platforms (Booking.com, Expedia, Airbnb) rather than domestic alternatives. These platforms capture **20–30% commission** on each transaction, meaning that digital infrastructure investment generates tourism demand but **fails to retain value domestically**. This contrasts with Morocco, where domestic platform ecosystems (e.g., Maroc Telecom's tourism portals) recapture a larger share of digital value.
3. **Absence of AI-native tourism applications:** While digital infrastructure enables **access** to algorithmic platforms, Algeria lacks **domestic AI deployment** in tourism. There are no locally developed dynamic pricing systems, no AI-powered recommendation engines for Algerian attractions, and no generative AI chatbots for multilingual tourist support (Nessaibi & Kermiche, 2025). The "Algorithmic Tourist" in Algeria is therefore **passively exposed** to global platform algorithms rather than **actively engaged** by destination-specific intelligent systems.

V.1.2. H2: The Failed Mediation and Its Implications

H2 (Mediation): Not supported (Sobel $z = 1.58$, $p = 0.115$). The indirect effect of Smart Destination Readiness on tourism through Algorithmic Tourist Engagement (ATEP) is **positive but statistically insignificant**. This is arguably the most theoretically significant finding of our study.

Why did mediation fail? The failure is not theoretical but **methodological**. Our ATEP proxy—constructed as Internet penetration $\times$ estimated online booking rate—is a **crude**

approximation of true algorithmic engagement. It captures **access** to algorithmic platforms but not **exposure intensity** (how many hours tourists spend on Instagram feeds, how deeply Booking.com's ranking algorithms influence their choices, how often Google's personalized search results redirect them toward Algerian destinations). These micro-behaviors are **unobservable with official statistics** and require primary data collection through:

- Tourist intercept surveys measuring platform usage intensity.
- Eye-tracking studies of Booking.com search result pages.
- Analysis of Instagram hashtag engagement (#VisitAlgeria, #AlgeriaTourism).
- Partnership with platforms for aggregated analytics (impossible with current data governance).

Theoretical implication: The H2 failure suggests that **infrastructure-to-engagement-to-demand** is not a simple linear pipeline. Instead, algorithmic mediation may operate as a **threshold effect**: below a critical digital infrastructure level, algorithmic engagement is negligible; above it, engagement explodes non-linearly. Algeria may currently operate **below this threshold**, explaining why infrastructure affects demand directly (through basic digital access) but not indirectly (through sophisticated algorithmic curation).

Policy implication: Policymakers should not interpret H2's non-support as evidence that algorithmic engagement is unimportant. Rather, it signals that **current measurement tools are inadequate** and that Algeria must invest in **tourism data infrastructure** before it can optimize algorithmic engagement strategies.

V.1.3. H3: Speed of Adjustment and Market Flexibility

H3 (Error correction): Strongly supported ($\phi = -0.457$, $p = 0.003$). The error correction coefficient indicates that **45.67% of disequilibrium** between digital infrastructure and tourism demand is eliminated within one year. This is **relatively rapid** compared to other structural economic adjustments:

Adjustment Type	Typical Speed	Algeria (This Study)
Tourism demand to infrastructure shocks	1.5–3 years	1.52 years (half-life)
Physical infrastructure (roads, airports)	5–10 years	—
Institutional change (visas, regulations)	3–5 years	—
Financial market adjustments	0.5–1 year	—

The 1.52-year half-life suggests that **Algerian tourism demand is digitally elastic**—tourists respond relatively quickly to connectivity improvements. However, the **ceiling effect** (elasticity capped at 0.343) indicates that this responsiveness is **bounded by supply constraints**: even if tourists want to visit Algeria in response to digital improvements, they cannot do so if hotel capacity, flight connections, and visa processing remain inadequate.

Comparison with regional peers: Morocco's error correction speed (estimated at 2.1 years by Ghomrani & Taamouti, 2016) is slower than Algeria's, suggesting that Morocco's more mature tourism market exhibits greater **institutional inertia**—established players resist rapid adaptation. Algeria's faster adjustment reflects its **emerging market status**: fewer legacy constraints allow more rapid demand response, albeit from a lower base.

V.1.4. H4: Cointegration and Structural Relationship

H4 (Cointegration): Strongly supported ($F = 4.87 > 4.35$ upper bound). The existence of a long-run cointegrating vector between digital infrastructure and tourism outcomes is **theoretically significant**. It confirms that Algeria's digital-tourism system is not merely **correlated** but **structurally linked**—shocks to infrastructure permanently alter the long-run tourism trajectory rather than causing temporary deviations.

Implications for SDAT 2030: The cointegration finding validates the government's strategic emphasis on digital transformation. However, it also implies that **digital infrastructure deficits are not easily reversible**: if Algeria fails to invest in connectivity now, the long-run

tourism trajectory will remain depressed. Conversely, sustained digital investment will yield **permanent** rather than temporary tourism gains.

V.2. The "Algorithmic Tourist" in Algeria: A Staged Reality

Our conceptual framework proposed the "Algorithmic Tourist" as travelers whose experiences are mediated by AI-driven personalization. The empirical evidence reveals a **staged reality** that falls short of this ideal:

Tier	Description	Evidence in Algeria	Prevalence	Policy Gap
Tier 1: Global Platform Algorithms	Booking.com ranking, Instagram feeds, Google search personalization	Confirmed: 67% of international bookings via Booking.com/Expedia; Instagram #VisitAlgeria has 45,000 posts but no official destination AI curation	High for international tourists	Value leakage to foreign platforms; no domestic algorithmic control
Tier 2: Basic Digital Mediation	Static websites, email booking, basic mobile apps	ANPT portal exists but lacks personalization; 12% of hotels offer online booking; no dynamic pricing	Medium for domestic tourists	Underinvestment in domestic platform ecosystems
Tier 3: AI-Native Personalization	Dynamic pricing, predictive recommendations, chatbot concierges, generative content	Absent: No domestic AI tourism deployment identified in 2024	Negligible	Absence of AI talent, data infrastructure, and R&D investment

Conclusion: Algeria's "Algorithmic Tourist" is predominantly **Tier 1**—international visitors processed by global platform algorithms. Domestic tourists experience **Tier 2** basic digitalization. **Tier 3** AI-native tourism remains **aspirational**, requiring 7–10 years of sustained investment.

V.3. Theoretical Contributions

V.3.1. Extending Smart Destination Theory to Data-Constrained Environments

Existing smart destination theory (Gretzel et al., 2015; Boes et al., 2017) assumes **abundant data availability** and **mature digital ecosystems**. Our study extends this framework to **transitioning economies** where:

- Official statistics are sparse (n = 15 observations).
- AI metrics are absent.
- Platform data is proprietary.
- Infrastructure is supply-constrained rather than demand-driven.

We demonstrate that **ARDL methods** can generate valid inferences in such environments, provided researchers (a) transparently acknowledge proxy limitations, (b) apply uncertainty quantification, and (c) avoid over-ambitious composite indices.

V.3.2. Refining the "Algorithmic Tourist" Construct

Our findings suggest that the "Algorithmic Tourist" should be **disaggregated** by **platform origin** (global vs. domestic) and **AI sophistication** (rule-based vs. machine learning):

- **Global-Algorithmic Tourist:** Exposed to Booking.com's collaborative filtering, Instagram's engagement-based ranking, Google's PageRank. **Value captured by foreign platforms.**
- **Domestic-Algorithmic Tourist:** Exposed to locally developed recommendation systems. **Value retained domestically.** (Absent in Algeria.).
- **AI-Native Tourist:** Engaged with generative AI, predictive analytics, autonomous service robots. **Value created through innovation.** (Absent in Algeria.).

This disaggregation has **policy relevance**: governments should prioritize **domestic platform development** before investing in frontier AI, as the former captures more value at lower cost.

V.4. Comparative Regional Analysis

Table 11: Digital Tourism Maturity Comparison: Algeria vs. Regional Peers

Dimension	Algeria	Morocco	Tunisia	Source
Tourism arrivals (2024)	3.5 million	14 million	9 million	UNWTO (2024)
Tourism GDP contribution	1.47%	8.2%	6.8%	WTTC (2024)
TTDI rank (2024)	113th	58th	75th	WEF (2024)
ICT readiness score	3.2/7	4.1/7	4.3/7	WEF (2024)
Internet penetration	71.2%	88.4%	79.1%	DataReportal (2024)
Digital-tourism elasticity	0.343	0.52	—	This study; Ghomrani & Taamouti (2016)
Domestic tourism platforms	Negligible	Moderate (Maroc Telecom)	Moderate (Tunisian Travel)	Industry reports
AI tourism applications	Absent	Emerging (pilot projects)	Emerging (chatbots)	Nessaibi & Kermiche (2025)

Key insight: Algeria's 3–5 year lag behind Morocco and Tunisia is **not primarily due to connectivity** (71% Internet penetration is respectable) but to **ecosystem maturity**: Morocco has developed domestic platforms, Tunisia has deployed government chatbots, while Algeria remains dependent on international platforms.

V.5. Methodological Reflection

V.5.1. ARDL Appropriateness for Small Samples

Our $n = 15$ sample pushes econometric boundaries. We selected ARDL over VAR for three reasons:

1. **Sample size efficiency:** VAR with 3 variables and 2 lags requires estimating 18 parameters, consuming 12 degrees of freedom—leaving only 3 for inference. ARDL(1,1,1) estimates 6 parameters, preserving 9 degrees of freedom.
2. **Mixed integration orders:** ARDL handles $I(0)$ and $I(1)$ variables simultaneously, avoiding pre-testing bias from differencing decisions.
3. **Bounds testing:** The F-test for cointegration does not require pre-specified integration orders, reducing specification error.

Limitations acknowledged: With $n = 15$, our tests have **low power** (80% power to detect only large effects, $d > 0.8$). The marginally significant $H1a$ ($p = 0.074$) may reflect Type II error rather than true absence of short-run effects. Wide confidence intervals (elasticity CI: 0.02–0.66) reflect genuine uncertainty, not model misspecification.

V.5.2. Proxy Variable Limitations

The ATEP construction illustrates **measurement without observation**:

$$ATEP_t = \left(\frac{Internet_t}{100} \right) \times \left(\frac{OnlineBooking_t}{100} \right)$$

Error propagation: If Internet penetration has $\pm 2\%$ measurement error and Online Booking has $\pm 20\%$ estimation error, the compounded ATEP uncertainty is approximately $\pm 20.1\%$. This classical measurement error biases the mediation coefficient toward zero (attenuation bias), explaining $H2$'s non-support.

Recommendation: Future research should replace ATEP with direct behavioral measures:

- Platform analytics (time spent on Booking.com Algeria pages).
- Social media engagement rates (likes, shares, saves on #VisitAlgeria).
- Search volume indices (Google Trends for "Algeria tourism").

V.6. Final Assessment

This study establishes that Algeria's smart destination transition is infrastructure-constrained, not demand-constrained. The 0.343 elasticity, while modest, is structurally significant: it confirms that digital investment yields permanent tourism gains, not temporary spikes. However, the absence of domestic AI deployment and dependence on international platforms means that Algeria captures only a fraction of the digital value it generates.

The "Algorithmic Tourist" in Algeria is therefore a work in progress—a traveler who encounters algorithmic mediation primarily through foreign platforms, lacking the personalized, culturally-grounded, AI-native experiences that could differentiate Algeria from competitors.

Closing this gap requires not more connectivity, but strategic ecosystem development that prioritizes domestic platforms, data infrastructure, and indigenous AI capabilities.

VI- Conclusion

This study establishes a modest, significant long-run association (elasticity 0.34) between digital infrastructure and tourism in Algeria (2010–2024), using ARDL methods appropriate for small samples. We transparently fail to fully operationalize the "Algorithmic Tourist" concept due to absent AI-tourism metrics, substituting proxied digital platform exposure with explicit uncertainty quantification.

The "Algorithmic Tourist" in Algeria remains aspirational. Current reality: "Platform-Mediated Tourist" exposed to global algorithms, not domestically AI-enabled experiences. The 0.34 elasticity provides empirical baseline for tracking transition to true algorithmic tourism.

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VIII-Appendices

Appendix A: Complete Data Table

Table A1: Annual Data 2010–2024

Year	Arrivals (000s)	Internet (%)	Mobile (/100)	SDR	ATEP (est.)	GDP pc (2015 US\$)	Ln(Arrivals)	Ln(GDP)
2010	2,070	12.5	92.1	0.122	0.031	4,213.5	7.635	8.346
2011	2,390	18.2	98.4	0.182	0.058	4,256.8	7.779	8.356
2012	2,630	25.4	102.3	0.253	0.091	4,289.3	7.875	8.364
2013	2,730	32.1	105.8	0.312	0.120	4,312.7	7.912	8.369
2014	2,290	38.2	108.9	0.368	0.152	4,334.2	7.736	8.374
2015	1,780	42.8	111.2	0.408	0.171	4,356.8	7.484	8.379
2016	2,030	48.9	113.5	0.467	0.215	4,378.4	7.616	8.384
2017	2,450	54.3	115.8	0.524	0.272	4,391.2	7.804	8.387
2018	2,660	59.7	116.9	0.576	0.334	4,405.6	7.886	8.391
2019	2,650	62.4	117.5	0.601	0.375	4,412.3	7.882	8.392
2020	591	65.1	118.2	0.627	0.416	4,123.6	6.382	8.324
2021	1,250	67.8	119.1	0.653	0.460	3,987.4	7.131	8.291
2022	2,300	69.5	119.8	0.672	0.500	4,102.3	7.741	8.319
2023	3,200	70.9	120.3	0.687	0.537	4,234.5	8.068	8.351
2024	3,500	71.2	120.8	0.691	0.569	4,356.2	8.161	8.379

Sources: World Bank WDI (2024), ITU (2024), UNWTO (2024), WTTC (2024). ATEP estimated as described in Section 3.3.

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