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Artificial intelligence as a catalyst for sustainable tourism growth and economic cycles

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ABSTRACT

We investigate the role of artificial intelligence (AI) in promoting sustainable tourism growth and its implications for the next technological and economic cycle. Focusing on the top ten global tourist destinations from 2010 to 2022, we investigate the interplay between AI adoption, gross domestic product (GDP), foreign direct investment (FDI), inflation (INF), and urbanization (UB). Utilizing a multi-method approach that integrates artificial neural network (ANN) analysis with traditional econometric models, the findings highlight that AI is a critical driver of tourism efficiency and smart tourism capabilities, significantly enhancing tourism sustainability. The study reveals substantial contributions from GDP, INF, FDI, and UB as well. AI's role as a pivotal technological catalyst in sustainable tourism development underscores its importance in shaping the next economic cycle. These insights provide essential guidance for policymakers and industry stakeholders on leveraging AI to propel tourism growth, aligning with broader goals of economic and environmental sustainability.

1. Introduction

The intersections of technology, energy transition, and economic sectors have garnered increasing attention, with tourism emerging as a major beneficiary of these evolving dynamics (Buhalis and Law, 2008; Vu and Hartley, 2022). Among technological advancements, artificial intelligence (AI) has been a pivotal force, providing novel insights and operational efficiencies across industries, including tourism (Huang et al., 2024; Ku and Chen, 2024; Pham et al., 2024; Rasheed et al., 2024; Scarpi, 2024). This study focuses on the role of AI adoption in driving tourism growth, specifically within the top ten tourist-receiving countries from 2010 to 2022. The tourism sector is not only a critical economic driver but also a catalyst for cultural exchange and global understanding (Alcalde-Giraudo et al., 2021; Cuomo et al., 2021; Koo et al., 2017; Vu and Hartley, 2022). Beyond technological advancements, tourism growth is influenced by economic indicators such as gross domestic product (GDP), inflation (INF), foreign direct investment (FDI), and urbanization (UB). The interplay of these variables offers rich insights into tourism growth patterns, particularly in the world's most visited nations (Can and Gozgor, 2018; Erdoğan et al., 2022). Moreover, as climate change progresses, energy transitions, and the rise of green finance become prominent. It is vital to understand how these factors shape the next wave of technological and economic cycles. AI, as a transformative technology, plays a crucial role in integrating with these broader economic and environmental shifts to influence sustainable tourism growth. This research investigates the synergistic effects between AI adoption and key economic indicators, revealing how they enhance tourism efficiency and resilience.

This study is timely, given the need for sustainable development strategies that support economic growth while addressing global environmental challenges. A focus on the top ten tourist-receiving countries is ideal for examining AI's impacts on tourism growth alongside other economic variables. These nations, due to their appeal and strategic efforts to attract tourists, significantly contribute to the global tourism economy. The sector, however, remains susceptible to various influences, including technological breakthroughs and macroeconomic trends. Historically, tourism growth has closely followed economic prosperity, with GDP serving as a reliable indicator not just of a destination's economic health, but also of its ability to draw tourists (Das et al., 2023; Meşter et al., 2023). Likewise, FDI has played a vital role in

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enhancing tourism infrastructure, making destinations more attractive to international visitors (Gopalan et al., 2023; Park, 2024). Additionally, inflation rates and urbanization levels interact with these factors, affecting travel costs and the quality of urban attractions (Chi, 2024; Hambarde and Shinde, 2024; Raifu and Afolabi, 2024). AI introduces a new dimension to these determinants, providing opportunities to improve visitor experiences, streamline operations, and create value (Ku and Chen, 2024; Samala et al., 2022).

Despite growing interest in the intersection of technology and tourism (Ahmad et al., 2022; Cuomo et al., 2021; Hadjielias et al., 2022; Kozłowski et al., 2021; Liu et al., 2018; Sharma et al., 2021) there remains a gap in the literature regarding AI's combined impact with traditional economic factors on tourism growth. Previous studies have often treated these factors separately, focusing on either technological or economic determinants (Antonakakis et al., 2019; Huang et al., 2024; Ku and Chen, 2024; Muyibul et al., 2023; Park, 2024). Additionally, the quantification of AI's direct impact on tourism growth, especially in the top tourist destinations, has been under explored. Our research aims to address this gap by answering the following questions: (1) What is the role of AI adoption in tourism growth in the top ten tourist countries? (2) How do AI, GDP, INF, FDI, and UB influence tourism growth in these nations? (3) How do determining factors interact to shape tourism growth patterns? To answer these questions, we utilize a conceptual framework based on research hypotheses to identify the impact of AI adoption on tourism growth, alongside the economic drivers that influence tourism growth in the top tourist-receiving countries from 2010 to 2022. These economic factors include GDP, INF, FDI, and UB, which collectively shape tourism patterns in these nations.

Our study makes significant contributions to the existing literature on tourism. First, it stands out as one of the pioneering investigations into the influence of AI adoption on tourism growth. Second, it offers a comprehensive analysis of the multifaceted impacts of AI adoption alongside key economic indicators such as GDP, INF, FDI, and UB on tourism growth, thus providing a holistic understanding of these interrelated factors. Methodologically, this research advances our understanding of the complex relationships between these variables by employing a multi-method approach that integrates machine learning-based artificial neural network (ANN) techniques with various econometric models. Further, the study offers practical implications for policymakers, regulators, and governments by highlighting strategies to enhance tourism growth through the synergistic utilization of both artificial intelligence and economic factors, thereby informing more effective policy decisions and interventions in the tourism sector.

The remainder of the study is organized as follows: Section 2 reviews relevant literature on AI and tourism growth. Section 3 details the methodology and data sources. Section 4 presents the empirical results and along with discussion. Section 5 discusses policy implications of while Section 6 concludes with recommendations for future research directions.

2. Literature review and hypotheses formulations

2.1. Association between AI adoption and tourism growth

AI refers to the simulation of human intelligence processes by machines, particularly computer systems, which can perform tasks that typically require human intelligence, such as problem-solving, decision-making, and learning (Haefner et al., 2023; Moravec et al., 2024). The integration of AI within the tourism sector represents a significant paradigm shift, enabling experiences that are increasingly personalized, efficient, and environmentally sustainable. This transformation is extensively documented in literature. For example, Huang et al. (2024) and Ku and Chen (2024) emphasize the profound impact of AI on both economic outcomes and customer satisfaction in the tourism industry. Additionally, as Ansari et al. (2022) suggest, AI not only reduces operational costs but also facilitates the emergence of innovative business models, marking a transformative period for the sector. AI has the potential to transition the industry from conventional to smart tourism, aligning closely with modern visitor demands for more tailored and sustainable travel experiences (Tussyadiah, 2020).

Moreover, AI technologies, ranging from chatbots to predictive analytics and customized travel solutions, play an instrumental role in enhancing customer service by catering to individual needs while promoting sustainability through adaptive practices. As a result, tourist satisfaction is significantly improved (Ansari et al., 2022). This development highlights AI's far-reaching influence, both in virtual and physical interactions, within the tourism sector. In addition to virtual interactions, AI is critical in enhancing digital connectivity in physical engagements, which enriches the hospitality experience. For instance, García-Madurga and Grilló-Méndez (2023) argue that AI is crucial in raising service standards, optimizing operations, and personalizing travel experiences. Consequently, this synergy between technology and tourism has reshaped the industry, positioning AI as a key driver of growth (Pinheiro et al., 2021). As AI capabilities advance, smart tourism, characterized by personalized experiences and greater operational efficiency, continues to grow in potential (Herrera et al., 2023). However, despite the clear advantages of AI, its adoption raises challenges. Stakeholders must carefully balance technological innovation with the preservation of human interaction in tourism (Sampaio et al., 2021). As Tussyadiah (2020) points out, the continued evolution of AI and related technologies is likely to accelerate the adoption of intelligent automation within tourism, further underscoring the trend of leveraging AI for industry growth. Given this substantial body of literature, we propose that AI adoption plays a critical role in driving tourism growth, highlighting the intersection of technological innovation and industry advancement.

H1. AI adoption significantly promotes tourism growth.

2.2. Association between GDP and tourism growth

The relationship between economic growth and tourism has been widely studied across different regions, consistently revealing patterns of interaction between international tourism and economic performance. Research highlights that global uncertainties, particularly economic and political instability, negatively affect tourism demand (Gozgor et al., 2021). Antonakakis et al. (2019) and Fawaz et al. (2014) identify a strong connection between tourism and economic growth that transcends differences in political systems, economic conditions, and tourism industry development across countries. The link between GDP and tourism growth is also influenced by economic cycles, with variable outcomes during periods of expansion and contraction. For instance, while tourism specialization may mitigate some positive-growth effects, increased tourism receipts typically bolster economic growth (Scarlett, 2021). The extent of tourism's impact on local income levels often depends on a country's development stage and infrastructure capacity (Jia et al., 2019).

Further insights are provided by Can and Gozgor (2018), who introduce a market diversification index, showing how diversified tourism arrivals positively influence economic growth. Panagiotou and Katrakilidis (2023) emphasize the complexity of the tourism-economic growth relationship, considering factors such as tourism specialization, globalization, and economic complexity. Antonakakis et al. (2019) find that tourism-driven growth is more prominent in developing, nondemocratic countries with low tourism specialization, while bidirectional growth dynamics are more evident in democratic nations with high governance effectiveness. Additionally, Figini and Patuelli (2022) and Badulescu et al. (2020) explore the long-term contributions of tourism to GDP, employment, and value added in EU countries, further highlighting tourism's economic significance. Despite the extensive research, a gap remains in understanding the direct correlation between GDP and the tourism sector in the world's leading tourist destinations.

This gap leads us to propose the following hypothesis:

H2. GDP significantly enhances tourism growth.

2.3. Association between FDI and tourism growth

Scholarly research on the effects of FDI on tourism growth presents a complex and sometimes contradictory picture. Some research underscores a beneficial influence of FDI on the tourism sector, while other studies present a more nuanced or negligible impact. Park (2024) finds that constraints on FDI are detrimentally linked to tourism development, suggesting that relaxations of FDI regulations enhance tourism sector growth. In support of this, Ağazade and Karasakaloğlu (2023) identify a positive correlation between FDI and various metrics of tourism success, such as the contribution of travel and tourism to GDP, international tourism receipts, and international tourist numbers. However, Mishra et al. (2020) find no significant effect of FDI on economic growth in India, attributing this to the relatively small volume of FDI directed toward the country's hotel and tourism sectors.

Soylu et al. (2023) extend the discourse to upper-middle-income nations, illustrating that while both FDI and tourism independently impact growth, the interaction between these factors produces asymmetrical outcomes, with tourism activity mitigating some of the negative repercussions of FDI on economic progress. Sokhanvar (2019) further contributes to the understanding of this relationship through a study on seven European Union countries, where significant portions of tourism receipts and FDI are integral to their economies, indicating a stimulatory effect of FDI on the tourism industry. Consequently, the body of research presents a dichotomy of perspectives regarding the influence of FDI on tourism growth, ranging from positive associations to minimal or context-dependent impacts. This divergence highlights the critical need to consider the unique economic, policy, and sectoral landscapes of individual nations when evaluating the potential effects of FDI on tourism expansion. Considering these mixed findings and the importance of contextual specificity, we propose the following hypothesis:

H3. FDI may have either a positive or negative impact on tourism growth.

2.4. Association between inflation and tourism growth

The relationship between inflation and tourism growth has been extensively analyzed, revealing predominantly negative correlations. A detailed empirical investigation within Nigeria's tourism sector (Raifu and Afolabi, 2024) reveals that inflation adversely impacts international tourist arrivals and tourism revenue. Complementing this, Shaari et al. (2018) explore the broader economic effects of tourism on inflation, identifying the tourism industry as a significant determinant of inflationary trends across both short and long temporal frames. These studies jointly suggest that inflation acts as a deterrent to international tourists, thereby diminishing tourism-generated income. The implications of these findings are economically significant, necessitating the implementation of preemptive strategies to ensure price stability and maintain inflation rates at levels conducive to the sustainable development of the tourism sector (Raifu and Afolabi, 2024; Shaari et al., 2018). Governmental interventions are recommended to mitigate inflationary pressures, thereby aiding the growth and expansion of the tourism industry (Shaari et al., 2018).

The mechanism through which inflation affects the tourism industry primarily involves the escalation of prices for goods and services utilized by tourists, potentially undermining their purchasing power. This dynamic could result in decreased tourist arrivals and lower tourism receipts, as detailed by Khan et al. (2022). Moreover, Raifu and Afolabi (2024) emphasize the pivotal role of price stability in fostering tourism. Inflation's impact extends to the reducing of international tourism flows, affecting both destination and origin countries, as highlighted by Khalid et al. (2020). The vulnerability of tourism to various external and internal economic shocks, including inflation, is further elaborated by Herman (2022), illustrating the potential for inflation to limit tourist demand and disrupt the economic stability of countries. High inflation rates are particularly problematic, leading to reduced foreign tourist spending, deterring international arrivals, and altering travel behaviors. Based on the above findings, it becomes apparent that inflation exerts a considerable negative influence on the growth trajectory of the tourism sector. This highlights the critical need for policy measures aimed at maintaining price stability as a cornerstone for facilitating tourism development. Accordingly, the following hypothesis is proposed:

H4. Inflation has a negative impact on tourism growth.

2.5. Association between urbanization and tourism growth

The relationship between urbanization and tourism growth has been verified through various scholarly investigations, underscoring a joint enhancement and dependency (Muyibul et al., 2023). The literature suggests that advancements in urbanization serve as a catalyst for the economic and environmental sustainability of tourism destinations, offering a robust economic foundation for tourism development (Muyibul et al., 2023). Recognized as a resource-conserving and environmentally benign industry, tourism significantly contributes to the refinement of urban industrial configurations, enlarges employment opportunities, and bolsters urban comprehensive capabilities and cultural legacy. Consequently, tourism has ascended as a pivotal industry in many cities, furnishing substantial benefits (Muyibul et al., 2023). Urbanization has prompted the transformation of existing tourist attractions and the creation of new ones, engendering scholarly discourse (Antić, 2020). The emergent trend of 'touristification,' portrayed as a socio-economic and spatial transfiguration process, has led to the predominance of a tourism monoculture within urban landscapes (Porfido et al., 2023). The clustering of tourism-related industries within cities manifests both agglomeration and congestion effects, influencing the overall productivity of urban agglomerates.

Moreover, the dynamics of urbanization exert an influence on tourist behaviors, such as destination attachment, where environmental modifications are observed to enhance tourists' affinity toward destinations (Huang et al., 2022). Tourism's role as a vital engine for economic and sociocultural progress is well acknowledged, with empirical evidence supporting its positive effects on socio-economic upliftment, poverty alleviation, inequality reduction, and the enhancement of living conditions for local populations. The impact of urbanization on tourism's economic growth is significant, with findings indicating that urbanization propels tourism development, albeit with regional variations. These differences highlight the necessity for policymakers to tailor their approaches to accommodate the distinct effects of urbanization on tourism growth in various locales (Luo et al., 2016). Despite the consensus on urbanization's positive influence on tourism development, the complexities associated with its cultural, environmental, and social implications warrant further examination, especially within the contexts of top-tourist destinations. This gap in empirical research underscores the need for a focused investigation into the role of urbanization in fostering tourism growth in such areas. Therefore, the following hypothesis is proposed:

H5. Urbanization significantly enhances tourism growth.

3. Methodology

3.1. Data

To examine the multifaceted impact of AI adoption and economic indicators (GDP, FDI, INF, and URB) on tourism growth, our study employs panel data spanning 2010 to 2022. The selection of sample and period is primarily dictated by the availability of comprehensive data on the variables, with a particular emphasis on the emerging role of artificial intelligence in the tourism sector. This period also coincides with significant global developments in AI technologies and their growing application across industries, including tourism. The years between 2010 and 2022 saw rapid advancements in AI, such as the rise of machine learning and natural language processing, which have directly impacted the efficiency and personalization of tourism services. Furthermore, this timeframe captures global tourism trends, such as the rapid increase in international tourist arrivals post-2010 and the recovery period following the COVID-19 pandemic, providing a comprehensive view of the evolving role of AI in tourism growth. Fig. 1 shows the number of AI startups in the top ten tourist countries from 2010 to 2022. The US and UK exhibit the most significant growth in AI startup adoption, particularly between 2015 and 2020, while some countries (e.g., Austria, Greece, and Mexico) show minimal change. Spain, France, and Germany exhibit moderate growth in AI startups over the same period, with slight fluctuations. The countries included in our analysis are identified by the United Nations World Tourism Organization (UNWTO) for the year 2022: Austria, France, Germany, Greece, Italy, Mexico, Spain, Turkey, the UK and the US. These countries together account for approximately 46 % of the global tourism industry, as shown in Fig. 2. This substantial market share highlights the importance of understanding the dynamics within these leading tourist destinations as they serve as bellwethers for global tourism trends and practices.

The significance of our study lies in several key areas. First, by focusing on the top ten tourist destinations, we provide insights into the tourism growth dynamics in countries that are pivotal to the global tourism economy. These nations not only attract the highest number of international visitors but also set trends in tourism management, sustainability practices, and technological integration, making them critical subjects for understanding broader industry patterns. Secondly, the integration of artificial intelligence into the tourism sector represents a cutting-edge area of research. Analyzing its impact, alongside traditional economic indicators, offers a holistic view of the future trajectory of tourism growth. Furthermore, understanding the effects of GDP, FDI, INF, and UB on tourism provides a comprehensive framework for policymakers and industry stakeholders in these countries to devise strategies that capitalize on strengths and address challenges. Lastly, given the significant contribution of these countries to global tourism, insights garnered from our study can inform international tourism policies and cooperation strategies, promoting sustainable growth and innovation in the sector worldwide.

Our dependent variable is tourism growth, measured by the number of international arrivals inbound, from UNWTO and WDI. The core independent variable of our study is AI adoption, as determined by the number of AI startups per year from *CrunchBase* (Fig. 1). *CrunchBase* is widely recognized for its extensive datasets on both private and public companies, offering detailed insights into startups, including their founding dates, industry sectors, and investment rounds (Mungo et al., 2024; Noguti et al., 2023). We collect and measure AI adoptions from *CrunchBase* based on several criteria: First, we select industry categories related to artificial intelligence startups. These include the following subgroups: ‘artificial Intelligence’, ‘generative AI,’ ‘intelligent systems,’ ‘machine learning,’ ‘natural language processing,’ ‘predictive analytics,’ and ‘robotic process automation’ (RPA). Second, we choose the timeframe of our study as 2010–2022 to measure AI adoptions in top tourist destinations. To ensure the accuracy and relevance of the data, we apply filtering criteria. We define AI startups as only active startups within the preceding categories, excluding those that did not meet our definition of AI-focused enterprises. We also take steps to eliminate duplicate entries and cross-referenced the data with additional sources where possible to validate the robustness of the dataset used for our analysis. The number of AI startups is chosen as a proxy for innovation and technological advancement, as it reflects the level of entrepreneurial activity and the adoption of AI technologies within the tourism industry. This data allowed us to assess the proliferation and integration of AI across different markets, serving as a concrete metric for their adoption within our study's framework.

Other variables, GDP, FDI, INF, and UB, are collected from *World Development Indicators*. Variable sources with their descriptions are highlighted in Table 1. While we acknowledge the potential influence of cultural and social variables on tourism growth, these factors are excluded in favor of focusing on quantifiable economic indicators that have a more direct and measurable impact on tourism growth. This decision aligns with existing literature, which considers the use of economic variables, such as GDP and FDI, as more robust and consistent determinants of tourism growth (Ağazade and Karasakaloğlu, 2023; Antonakakis et al., 2019; Fawaz et al., 2014). Incorporating cultural or

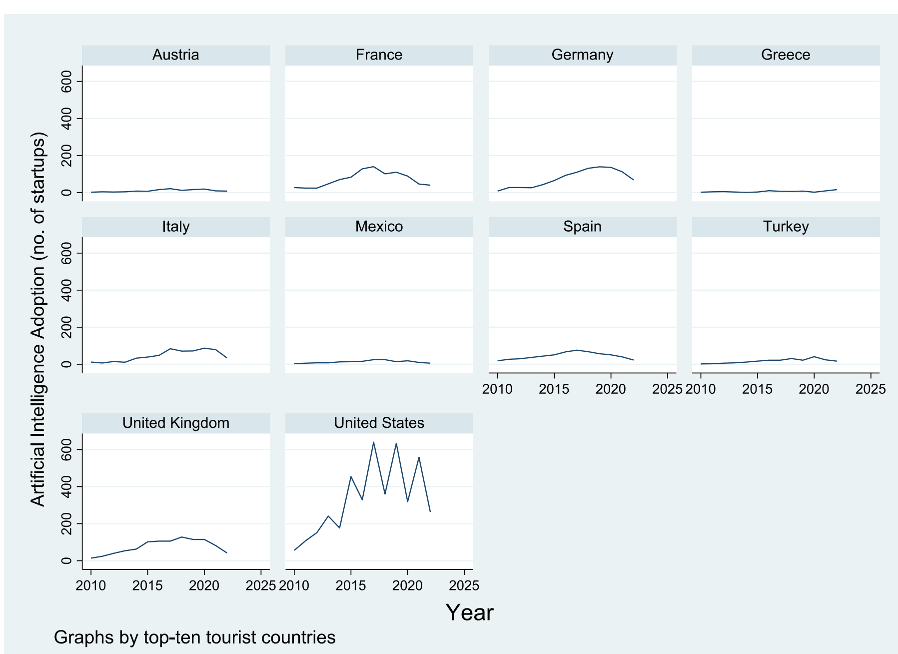

Fig. 1. Trend of AI adoptions by country over the years.

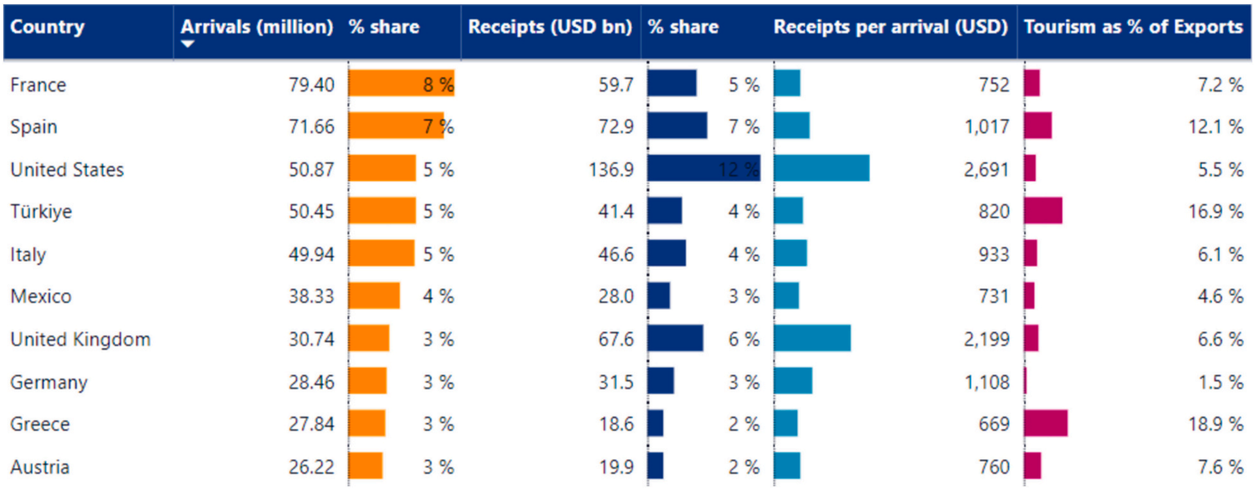

Fig. 2. Top ten countries for international tourist arrivals, receipts, and export revenues in 2022, sourced from UNWTO.

Table 1
Variables and description.

Variables	Abbreviation	Description	Sources
Tourism growth	TRSM	Number of arrivals inbound.	UNWTO and WDI
Artificial intelligence	AI	The number of AI startups per year.	Crunchbase
Gross domestic product	GDP	GDP per capita (constant 2015 US$).	WDI
Foreign direct investment	FDI	Foreign direct investment, net inflows (% of GDP).	WDI
Urbanization	UB	Urban population (% of total population).	WDI
Inflation	INF	Inflation (annual%).	WDI

Notes: UNTWO: United Nations World Tourism Organization; WDI: World Development Indicator.

social variables introduces complexities that detract from measuring economic outcomes. Summary statistics are shown in Table 2.

3.2. Data analysis techniques

A comprehensive multi-methods approach is employed to explore the dynamics of tourism growth in the top-ten countries, as well as to test the study's hypotheses. Our baseline model is specified by Eq. (1):

$$\mathrm{lTRSM}_{it} = \beta_o + \beta_1 \mathrm{AI}_{it} + \beta_2 \mathrm{lGDP}_{it} + \beta_3 \mathrm{lFDI}_{it} + \beta_4 \mathrm{lINF}_{it} + \beta_5 \mathrm{lUB}_{it} + \varepsilon_{it} \quad (1)$$

where:

- lTRSM_{it} represents the natural logarithm of tourism growth for country $_i$ at time $_t$.
- β_o is the intercept, which indicates the expected level of tourism growth when all independent variables are at their baseline or zero value in logarithmic terms.
- β_1 through β_5 are the coefficients capturing the marginal effects of the independent variables: AI (AI adoption), lGDP (logarithm of gross domestic product), lFDI (logarithm of foreign direct investment), lINF (logarithm of inflation), and lUB (logarithm of urbanization) on tourism growth. These coefficients represent the elasticity of tourism growth with respect to each variable, meaning a 1 % change in any independent variable corresponds to a percentage change in tourism growth, holding other factors constant.
- ε_{it} is an error term, capturing unobserved factors and potential measurement errors that may affect tourism growth but are not included in the model.

This baseline model serves as the foundation for our empirical analysis, aiming to quantify the contributions of technological advancement, economic performance, investment flows, price stability, and urban development to tourism industry growth.

Initially, we investigate using artificial neural networks (ANN), a machine learning technique known for its ability to model complex relationships and identify influential variables without making assumptions about their nature or interconnections (Hopfield, 1982; Leong et al., 2019b; Tian et al., 2023). We specifically choose ANN over other potential methods, such as random forests or support vector machines (SVM), because ANN excels at capturing complex, non-linear relationships between variables. This is particularly important in tourism growth analysis due to diverse and interdependent factors. Unlike models such as SVM, ANN does not require assumptions about variable interconnections, making it well-suited for modeling the complex dynamics between AI adoption, GDP, FDI, INF, UB, and tourism growth.

In the context of ANN analysis, the variables (AI, GDP, FDI, INF, and UB) and the target output (TRSM) are fed into the network as input and output layers, respectively. Each independent variable becomes a node in the input layer of the ANN. These variables do not need to be linearly related to the output, as the ANN can model complex, nonlinear relationships (Hew et al., 2023; Leong et al., 2019b; Tian et al., 2023). Between the input and output layers, one or more hidden layers can

Table 2
Descriptive statistics.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
lTRSM	10.893	10.673	12.292	8.762	0.813	−0.033	2.317
AI	69.054	27.000	640.000	1.000	111.535	3.375	15.459
lGDP	28.076	28.050	30.671	25.944	1.186	0.268	3.050
lFDI	1.123	1.301	3.186	−2.687	0.927	−2.070	8.509
lINF	0.744	0.727	4.281	−3.283	1.149	−0.613	5.088
lUB	4.328	4.365	4.436	4.045	0.102	−1.711	4.972

capture complex interactions among the inputs (Hew et al., 2023; Lee et al., 2020; Morales-Alonso and Núñez, 2022). The number of hidden layers and the number of nodes within each layer are parameters that can be adjusted based on the problem's complexity and the amount of available data (Lee et al., 2020; Tan et al., 2014). The target variable (TRSM) forms the output layer. Fig. 3 shows the structure of the ANN model used in this study to predict tourism growth.

Furthermore, to examine the study's hypotheses, four econometric models are utilized: pooled OLS estimation, which combines cross-sectional and time-series data into a single model assuming homogeneity across entities (Pesaran and Zhou, 2018); panel corrected standard errors (PCSEs), which adjust for cross-sectional dependence and heteroskedasticity in panel data (Beck and Katz, 1995; Breitung et al., 2022; Pesaran, 2006); and cross-sectional time-series feasible generalized least squares (FGLS) regression, which is designed to correct for both heteroskedasticity and autocorrelation in panel data (Moundigbaye et al., 2020), thereby improving efficiency. Moreover, to boost the validity of the findings from the OLS, PCSEs and FGLS analyses, dynamic panel-data estimation via a two-step system generalized method of moments (GMM) is applied. This method is particularly effective in addressing potential endogeneity issues by using lagged variables as instruments, thus providing a robust framework for causal inference in the presence of dynamic relationships (Arellano and Bond, 1991; Han and Renault, 2020; Hansen, 1982; Kim, 2020). Together, these methods offer a thorough investigation into the factors affecting tourism growth and the validity of the study's hypotheses, leveraging both the predictive power of machine learning and the rigorous inferential capabilities of econometric modeling.

4. Results and discussion

4.1. Artificial neural network analysis

To explore the determinants of tourism growth, we undertake ANN analysis, incorporating variables AI adoption, GDP, FDI, INF, and UB as input variables. Scholars (Leong et al., 2019a; Núñez and Morales-Alonso, 2024; Tian et al., 2023) advocate for ANN as modeling human neural networks in their capability to learn and assimilate new knowledge. This attribute allows ANNs to be trained, enhancing its predictive performance. A standard architecture of a multi-layer perceptron ANN consists of input, hidden, and output layers, as outlined by researchers (Leong et al., 2019a; Siddik et al., 2023). These layers are comprised of neuron nodes interconnected through synaptic weights, which adjust during learning phases via non-linear activation functions to meet specific objectives, as described by Núñez and Morales-Alonso (2024) and Siddik et al. (2023). Accordingly, employing a deep learning approach facilitates the attainment of more precise outcomes, leading our study to adopt an ANN configuration with a singular hidden layer, following the methodologies of (Morales-Alonso and Núñez, 2022; Núñez and Morales-Alonso, 2024).

Our analysis utilizes the back-propagation algorithm to reduce errors throughout the deep learning process, as described by Leong et al. (2019a) and Morales-Alonso and Núñez (2022). To ensure the robustness of the model and prevent overfitting, we implement a 10-fold cross-validation technique. This approach divides the dataset into ten subsets, iteratively training the model on nine subsets while testing it on the remaining one, which enhances the model's generalization ability. Additionally, a data training-to-testing ratio of 8:2 is maintained, following the recommendations of Leong et al. (2019a) and Siddik et al. (2023). These measures, along with cross-validation, help minimize the risk of overfitting and ensure that the results are reliable and robust. By adopting these strategies, the analysis successfully balanced model complexity with the prevention of overfitting, which reassures the validity of the findings.

The study's network architecture is detailed in Table 3. In addition, Fig. 4 shows the outcomes of the ANN model for predicting tourism growth. Evaluating the predictive accuracy of the ANN involved calculating root mean squared error (RMSE) values, which derive from the sum of squared errors (SSE) and should be minimal to indicate high prediction accuracy, as advocated by studies of (Hew et al., 2023; Lee et al., 2020; Tian et al., 2023). Additionally, the study assessed goodness-of-fit using the R^2 index, as suggested by Hew et al. (2023) and Leong et al. (2019a), to further validate predictive accuracy. The goodness-of-fit index (R^2) = 1- Average of RMSE during testing/Average of SSE during testing.

After constructing a singular deep learning ANN model for tourism growth, with inputs including AI, GDP, FDI, INF, and UB, the model demonstrates remarkable predictive accuracy, as evidenced by low RMSE values during both training and testing phases, detailed in Table 4. The model achieves an R^2 value of 0.935, signifying exceptional predictive accuracy. Due to this high level of accuracy, a sensitivity analysis was conducted for the ANN model, as depicted in Table 5. This

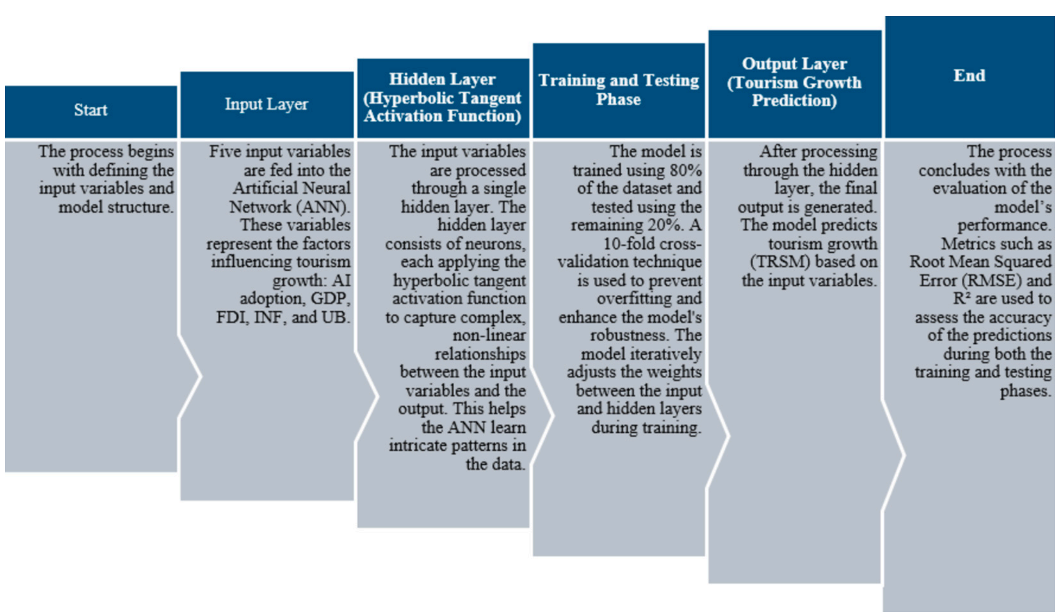

Fig. 3. ANN model architecture for predicting tourism growth with input variables AI, GDP, FDI, INF, and UB.

Table 3
Network architecture.

Models	Variables	Network configuration	Partition (%)	Activation function hidden layer	Activation function output layer
ANN1	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 80 Testing: 20	Hyperbolic tangent	Identity
ANN2	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 73.1 Testing: 26.9	Hyperbolic tangent	Identity
ANN3	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 79.2 Testing: 20.8	Hyperbolic tangent	Identity
ANN4	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 78.5 Testing: 21.5	Hyperbolic tangent	Identity
ANN5	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 76.2 Testing: 23.8	Hyperbolic tangent	Identity
ANN6	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 83.8 Testing: 16.2	Hyperbolic tangent	Identity
ANN7	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 69.2 Testing: 30.8	Hyperbolic tangent	Identity
ANN8	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 80.8 Testing: 19.2	Hyperbolic tangent	Identity
ANN9	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 83.1 Testing: 16.9	Hyperbolic tangent	Identity
ANN10	TRSM, AI, GDP, FDI, UB, INF	5-(3)-1	Training: 81.5 Testing: 18.5	Hyperbolic tangent	Identity

analysis revealed GDP as the most influential input variable on tourism growth, followed by inflation, AI, FDI, and UB, underscoring the differential impact of these variables on the tourism sector's expansion.

4.2. Econometric models

We scrutinize the linear correlations between AI, lTRSM, and key economic indicators, including lGDP, lFDI, lINF, and lUB as evidenced by a correlation matrix in Table 6. This matrix reveals correlations ranging from −1 to 1, indicating various degrees of relationship strengths and directions among the variables. Simultaneously, we evaluate the presence of multicollinearity through examining variance inflation factors (VIF). These remain below the commonly accepted threshold of 5 across all variables, indicating an acceptable level of multicollinearity (Hair et al., 2012; Henseler et al., 2009). Notably, urbanization (lUB) has the highest VIF value at 2.08, marking it as the most affected by multicollinearity, but still within acceptable limits, as shown in Table 6. The relatively low VIF values across the other variables (e.g., AI with a VIF of 1.13 and GDP with a VIF of 1.52) indicate that multicollinearity is not a major concern in our model, ensuring the reliability of our results. By combining correlation coefficients and VIF values, we seek to understand the interrelationships among these economic indicators, thus ensuring the robustness and reliability of our econometric modeling in explaining the dynamics between AI adoption, tourism growth, and economic factors.

In our investigation into the factors influencing tourism growth, we employ a set of econometric models, notably pooled OLS, PCSEs, FGLS, and a 2-step System GMM. Our analysis consistently identified AI and GDP as significant positive determinants of tourism growth across various models, underscoring their pivotal roles, thus supported H1 and H2 (see Tables 7 and 8). Conversely, the effect of FDI on tourism growth was found to be statistically insignificant in most models, suggesting its impact may be more complex or minimal, rejecting H3. The relationship between inflation and tourism growth predominantly appeared negative, with significance in all models except the FGLS, indicating that higher inflation may be detrimental to tourism. This indicates H4 is supported. Additionally, urbanization UB demonstrated a potential positive influence on tourism growth in the PCSEs model, implying that urban development could strengthen the sector.

For the robustness of our findings, we specifically utilized the 2-step System GMM analysis as shown in Table 8. This advanced method, which addresses issues of endogeneity and potential biases inherent in dynamic panels, affirmed the significant positive effects of AI and GDP on tourism growth. The 2-step System GMM results reinforce the robustness of these findings, while offering a complex perspective on the roles of FDI and UB, which did not consistently show significance across different models. Therefore, H5 is not supported. This layered approach, integrating varied econometric methodologies, ensures a comprehensive understanding of the complex dynamics at play in tourism growth and emphasizes the importance of methodological rigor in empirical research.

5. Discussions

We explore the role of AI adoption in tourism growth within the top ten tourist countries during the period 2010–2022. Additionally, we examine the multifaceted impacts of AI, GDP, INF, FDI, and UB on tourism growth. To achieve these objectives, we utilize a multi-methods approach, including machine learning-based ANN analysis and several econometric models. Our empirical findings contribute to the literature on technological innovations in artificial intelligence and the economic-tourism growth nexus in several ways. Firstly, this is among the pioneering studies to explore the impact of AI adoption on tourism growth in top-tourist countries. Hence, our study aims to fill this gap by examining the role of AI adoption in promoting tourism growth. Empirical findings from the ANN analysis confirm that GDP was the most influential factor of tourism growth, followed by INF, AI, FDI, and UB. This indicates that besides the potential impact of economic indicators on tourism growth, technological advancement such as AI adoption also plays a critical role in promoting tourism growth in top tourist destinations. Moreover, findings from several econometric analyses support the notion that AI adoption significantly and positively promotes tourism growth in top tourist destinations. The literature demonstrates that AI is transforming the tourism industry by enabling businesses to save money on operations and maintenance, leading to the creation of new business models (Ansari et al., 2022).

Secondly, our analysis of the multifaceted impacts of AI adoption, alongside key economic indicators such as GDP, Inflation, FDI, and UB on tourism growth, provides a holistic understanding of these interrelated factors within a single study. Our findings confirm that AI adoption and GDP are significant positive determinants of tourism growth. Literature finds that the relationship between international tourism and economic growth is consistent among different types of regions and countries, regardless of their economic, political, and tourism status (Antonakakis et al., 2019; Badulescu et al., 2020; Fawaz et al., 2014). Conversely, the effect of FDI on tourism growth was found to be statistically insignificant in most models, suggesting its impact might be more complex or minimal. The literature demonstrates mixed findings regarding the nexus between FDI and tourism growth. We find that FDI restrictions have a significant negative effect on tourism growth, implying that liberalizing FDI policies promote tourism growth (Park,

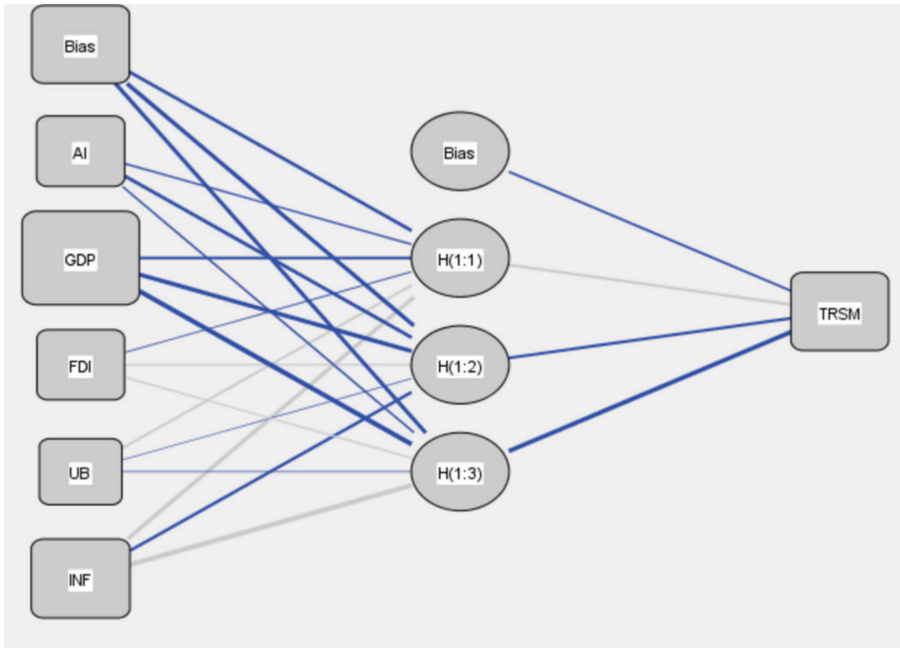

Fig. 4. Outcomes of ANN model for predicting tourism growth.

Table 4
Predictive accuracy of the ANN models.

Neural networks	ANN Model (R^2 = 0.935) Output neuron: TRSM					
	Input neuron: AI, GDP, FDI, UB, INF					
	Training			Testing		
	n	SSE	RMSE	n	SSE	RMSE
ANN1	104	25.508	0.495	26	9.413	0.602
ANN2	95	18.56	0.442	35	14.075	0.634
ANN3	103	23.328	0.476	27	8.302	0.555
ANN4	102	27.644	0.521	28	7.645	0.523
ANN5	99	24.746	0.500	31	5.347	0.415
ANN6	109	33.369	0.553	21	7.436	0.595
ANN7	90	20.661	0.479	40	11.227	0.530
ANN8	105	27.574	0.512	25	8.291	0.576
ANN9	108	25.929	0.490	22	3.456	0.396
ANN10	106	27.064	0.505	24	6.645	0.526
Average		25.438	0.497		8.184	0.535
Standard Deviation		4.086	0.030		2.965	0.077

Note: $\mathrm{RMSE} = \sqrt{\left(\frac{1}{n}\right) \times SSE}$.

Table 5
The sensitivity analysis.

Neural networks	Output neuron: TRSM				
	Relative Importance				
	GDP	INF	AI	FDI	UB
ANN1	1.000	0.443	0.041	0.340	0.299
ANN2	1.000	0.737	0.558	0.162	0.039
ANN3	1.000	0.824	0.310	0.667	0.364
ANN4	1.000	0.426	0.323	0.436	0.153
ANN5	1.000	0.689	0.545	0.513	0.322
ANN6	1.000	0.371	0.988	0.383	0.734
ANN7	1.000	0.516	0.653	0.383	0.365
ANN8	1.000	0.494	0.449	0.222	0.145
ANN9	1.000	0.824	0.221	0.340	0.603
ANN10	1.000	0.584	0.715	0.510	0.270
Average relative importance	1.000	0.591	0.480	0.396	0.329
Normalized relative importance (%)	1.000	0.591	0.480	0.396	0.329
Rank	1st	2nd	3rd	4th	5th

2024). In contrast, Ağazade and Karasakaloğlu (2023) find that FDI positively affects various tourism performance indicators, including travel and tourism GDP, international tourism receipts, and international tourist arrivals. The discrepancies between our findings and those of Ağazade and Karasakaloğlu (2023) may be attributed to differences in geographical focus, as our study concentrated on the top ten tourist destinations globally, while other studies focus on different regions with varying levels of FDI flows and tourism infrastructure. Additionally, differences in studied time periods could influence the role of FDI in tourism growth, as shifts in global economic conditions and FDI policies may affect its impact over time. However, a study focusing on India did not find any significant impact of FDI flows to the tourism sector on the economic growth of the country, possibly due to the low quantum of FDI equity flows to the hotel and tourism sector in India (Mishra et al., 2020).

Furthermore, the relationship between inflation and tourism growth predominantly appeared negative, indicating that higher inflation may be detrimental to tourism. This relationship is supported by existing studies (Raifu and Afolabi, 2024; Shaari et al., 2018). These findings suggest that inflation can dissuade international tourist arrivals and lower tourism revenue. Additionally, we find mixed results for urbanization development and tourism growth; only a single model demonstrates a positive and significant impact, while others confirm a positive association but insignificant, implying that urban development could strengthen the sector. Recent literature has demonstrated that tourism and urbanization are closely related (Muyibul et al., 2023). The literature exhibits that urbanization is conducive to promoting the economic and environmentally sustainable development of tourism destinations. Urbanization provides a good economic basis for the development of tourism (Muyibul et al., 2023).

6. Implications

6.1. Implications for economic and technological cycles

Our findings have significant implications for both economic and technological cycles in the tourism industry. The positive impact of AI

Table 6
Correlation matrix and VIF values.

	lTRSM	AI	lGDP	lFDI	lINF	lUB	VIF	1/VIF
lTRSM	1						1.56	0.639
AI	0.319	1					1.13	0.882
lGDP	0.520	0.132	1				1.52	0.659
lFDI	0.108	0.031	0.260	1			1.55	0.646
lINF	−0.326	−0.280	−0.164	0.067	1		1.12	0.892
lUB	0.315	−0.064	0.542	0.580	−0.003	1	2.08	0.481

Table 7
Outcomes of pooled OLS and PCSEs.

Variables	Coefficient	Std. errs.	*z*-value	*p*-value	[95 % conf. interval]	
Outcomes of Pooled OLS						
AI	0.002**	0.001	2.880	0.005	0.001	0.003
lGDP	0.272***	0.063	4.280	0.000	0.146	0.397
lFDI	−0.073	0.079	−0.920	0.358	−0.229	0.083
lINF	−0.134**	0.055	−2.450	0.016	−0.243	−0.026
lUB	1.271	0.812	1.560	0.120	−0.338	2.879
Outcomes of PCSEs						
AI	0.002**	0.001	2.760	0.006	0.000	0.003
lGDP	0.272***	0.027	10.130	0.000	0.219	0.324
lFDI	−0.0738*	0.044	−1.660	0.097	−0.158	0.013
lINF	−0.134**	0.054	−2.510	0.012	−0.239	−0.030
lUB	1.271**	0.421	3.020	0.003	0.446	2.095

*** $p < .01$.
** $p < .05$.
* $p < .1$.

Table 8
Outcomes of FGLS and 2-step System GMM.

Variables	Coefficient	Std. errs.	*z*-value	*p*-value	[95 % conf. interval]	
Outcomes of FGLS Regression						
AI	0.002**	0.001	2.950	0.003	0.001	0.003
lGDP	0.272***	0.062	4.390	0.000	0.150	0.393
lFDI	−0.073	0.077	−0.950	0.344	−0.223	0.078
lINF	−0.134**	0.054	−2.510	0.012	−0.239	−0.030
lUB	1.271	0.791	1.610	0.108	−0.280	2.821
Outcomes of 2-step System GMM						
AI	0.001**	0.000	4.040	0.003	0.001	0.002
lGDP	0.378**	0.094	4.020	0.003	0.165	0.591
lFDI	−0.031	0.085	−0.360	0.724	−0.222	0.161
lINF	−0.129**	0.056	−2.320	0.045	−0.255	−0.003
lUB	1.195	4.014	0.300	0.773	−7.885	10.275

hansenp: 0.978.
*** p < .01.
** p < .05.

adoption on tourism growth suggests that advancements in technology are key drivers in shaping the future of tourism. As AI enhances operational efficiencies, personalizes tourist experiences, and promotes sustainability, its integration within tourism aligns with broader technological cycles that foster innovation and smart services. In periods of rapid technological development, such as the current AI-driven era, tourism businesses that adopt these technologies can gain a competitive advantage, fueling growth and contributing to the overall economic cycle. From an economic perspective, the role of GDP as the most influential factor in tourism growth underscores the importance of a stable and expanding economy. When economies are in growth phases, higher disposable incomes and stronger infrastructure investment, fueled by GDP increases, can stimulate tourism demand. Conversely, inflation, which negatively affects tourism, indicates that economic downturns or periods of rising costs can deter international visitors, reducing revenues and slowing tourism growth. Therefore, policymakers must focus on maintaining economic stability and fostering technological innovation to ensure that tourism remains resilient across different phases of economic and technological cycles. Therefore, the intertwined effects of AI adoption and economic indicators like GDP and inflation reveal the dual importance of technology and economic policy in sustaining tourism growth through varying economic and technological cycles. Policymakers and industry stakeholders should leverage these insights to drive future strategies that integrate technological advancements with sound economic planning to bolster the tourism sector.

6.2. Practical implications

Our study's findings offer several practical and policy implications, providing valuable insights for stakeholders within the tourism sector, as well as for policymakers and governments of top tourist destinations. First, the positive impact of AI adoption on tourism growth highlights the importance of investing in AI technologies. These investments can enhance customer experiences, improve operational efficiencies, and facilitate the creation of innovative business models. Governments and industry stakeholders should prioritize the integration of AI into tourism services to foster growth and competitiveness. For instance, Spain has successfully leveraged AI to navigate the challenges of the post-COVID-19 era. AI was employed to solve issues arising from mask mandates by enabling seamless communication through advanced AI systems, thereby improving visitor experiences despite pandemic-related restrictions (Torres-Penalva and Moreno-Izquierdo, 2024). Additionally, Spain has integrated AI-driven data analytics and predictive systems to manage tourist inflows and improve sustainability in cities like Barcelona. By doing so, local authorities were able to control overcrowding in tourist hotspots, enhance visitor experience, and reduce the strain on infrastructure. This demonstrates how AI can be applied effectively to address both economic and environmental challenges in tourism management.

Second, our analysis reveals that GDP is the most significant factor influencing tourism growth, underscoring the pivotal role of economic development as a catalyst for the tourism sector. This suggests that policies aimed at overall economic stability and growth are crucial, as they create a conducive environment that attracts tourists by increasing disposable income and encouraging infrastructure development. Third, the study's findings on the negative impact of inflation on tourism growth indicate the need for policies that aim to control inflation. Such measures can make destinations more attractive to international tourists by ensuring price stability for tourism-related services and products, thereby enhancing the sector's growth prospects.

Fourth, given the mixed findings regarding the impact of FDI on tourism growth, there is a clear need to re-evaluate and potentially liberalize FDI policies in the tourism sector. Encouraging foreign investment can lead to increased capital flow into tourism infrastructure, technology, and services, which is essential for the sector's development and competitiveness. Fifth, the mixed impact of urbanization on tourism growth calls for policies that support sustainable urban development. Since urban areas often serve as major tourist attractions, developing infrastructure, services, and amenities in these areas can attract more tourists. However, it is essential to ensure that such development is sustainable and does not adversely affect the environment or local communities. Finally, our study's methodological approach, integrating machine learning techniques with traditional econometric models, highlights the importance of continuous research and development. This approach underlines the need for academia and industry to collaborate closely on future studies, further explaining the complex interplays affecting tourism growth. By adopting a holistic approach that addresses these factors, countries can foster a more robust, sustainable, and innovative tourism sector, contributing significantly to economic development.

6.3. Social implications

Our findings have several important social implications, particularly regarding the role of AI in transforming the tourism sector. As AI adoption becomes more widespread, it can enhance the overall travel experience, making it more accessible, personalized, and sustainable. This shift can lead to greater inclusivity, allowing more individuals from diverse backgrounds to participate in tourism through easier access to information, tailored services, and reduced costs. AI-driven tourism can also help alleviate environmental pressures, promoting sustainable practices that benefit local communities by reducing resource consumption and minimizing negative environmental impacts. However, the widespread adoption of AI also raises concerns about job displacement within the tourism industry, as automation replaces certain roles traditionally performed by humans. This potential shift necessitates a focus on upskilling the workforce to ensure that employees can adapt to new AI-driven technologies, fostering a more resilient and future-proof labor market. Additionally, the negative effects of inflation on tourism, as observed in the findings, highlight the need for policies that address economic inequalities, ensuring that the benefits of tourism growth are distributed equitably across society. As a result, the integration of AI in tourism has the potential to improve social inclusivity, sustainability, and economic equity, but it also requires thoughtful management of workforce transitions and economic disparities to ensure that the social benefits are fully realized.

7. Conclusions

We offer a pioneering examination of the impact of AI adoption on tourism growth across major global destinations from 2010 to 2022, utilizing a novel blend of machine learning and econometric models. We evidence that AI has a significant positive role in promoting smart tourism and operational efficiencies underscores its transformative potential (Huang et al., 2024). We also find that GDP growth, inflation, FDI, and urbanization have important influence. Notably, our findings suggest complex relationships between FDI, INF, and tourism growth, with INF negatively affecting tourism and FDI's impact being context dependent. Urbanization's contribution to tourism growth further illustrates the interconnection between urban development and the tourism industry. Methodologically, our study advances scholarly understanding by integrating machine learning with traditional analyses, offering new insights into the dynamics driving tourism growth and providing valuable implications for policymakers and industry stakeholders in leveraging technology for tourism development.

This study has limitations that should be acknowledged to provide a more transparent and balanced conclusion. First, the study's timeframe (2010–2022) may not fully encapsulate the enduring impacts of AI adoption on tourism growth. Future research could explore the long-term impacts of AI adoption on tourism beyond 2022, providing insights into how AI continues to shape the industry over extended periods. Second, the reliance on ANN and econometric models could omit alternative analytical perspectives crucial for a more rounded understanding. Third, focusing on top ten tourist destinations limits the applicability of findings across different tourism contexts globally. Future studies should consider expanding the analysis to include less visited or emerging tourist destinations to understand the broader applicability of AI in various tourism settings.

Additionally, the data collected from *CrunchBase* for AI startups, while comprehensive, may have geographical limitations, as it may not fully capture emerging AI startups in less digitized regions or developing countries. Potential reporting delays or incomplete records may also impact the findings. Future research should aim to address these limitations by incorporating data from more diverse sources or regions to capture a broader spectrum of AI adoption. Furthermore, there is potential for bias in AI startup data, as the availability and accuracy of such data may vary across regions. Moreover, measuring AI's direct impact on tourism growth poses challenges due to the indirect and multifaceted ways AI influences the sector. Future research could also examine the interplay between AI and non-economic factors, such as cultural influences or political stability, to provide a more comprehensive understanding of how these variables shape tourism trends. Fourth, while economic indicators are analyzed, other influential factors like environmental sustainability and political stability are overlooked. Lastly, due to our research framework, we did not account for control variables such as governance quality, environmental policies, or technological infrastructure, which may have influenced the relationship between AI adoption and tourism growth. The absence of these variables could limit the depth of our findings by overlooking important mediators that might affect both AI implementation and tourism sustainability. Future research should incorporate such control variables, as well as factors like political stability, technological readiness, and cultural influences, to offer more comprehensive insights into the role of AI and the broader contextual factors that drive sustainable tourism growth.

CRediT authorship contribution statement

Abu Bakkar Siddik: Writing – original draft, Formal analysis, Data curation, Conceptualization. **Md. Shak Forid:** Writing – original draft, Software, Methodology, Data curation. **Li Yong:** Writing – original draft, Validation, Software. **Anna Min Du:** Writing – review & editing, Supervision, Project administration, Investigation, Conceptualization. **John W. Goodell:** Writing – review & editing, Validation, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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