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CONTENTS

AI FRAMEWORK FOR ASSESSING THE IMPACT OF GEOPOLITICAL RISK ON GLOBAL TOURISM DEMAND

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Abstract

Purpose – This study introduces and illustrates an AI-based framework for assessing the impact of geopolitical risk on global tourism demand. It examines how a tourism-specific risk measure can be combined with heterogeneous economic, spatial, and behavioral indicators.
Methodology – The study applies a multi-source quantitative approach using tourism, macroeconomic, geopolitical, spatial, and Google Trends data. A composite Geopolitical Tourism Risk Index (GTRI) is constructed to capture destination-specific exposure. XGBoost serves as the AI analytical tool for processing heterogeneous indicators and identifying nonlinear relationships and interactions.
Findings – The illustrative application shows that geopolitical instability is associated with differentiated tourism-demand responses across destinations. The GTRI supports the assessment of risk exposure, tourism-flow redistribution, and delayed demand responses. The XGBoost application demonstrates the feasibility of integrating heterogeneous determinants within a unified analytical framework.
Originality of the research – The study introduces a tourism-specific Geopolitical Tourism Risk Index (GTRI) integrated into an AI-based tourism demand forecasting framework. The originality lies in combining geopolitical risk, spatial proximity, tourism dependence, behavioral risk perception, and conventional tourism indicators, while XGBoost functions as a flexible tool for their joint analysis.
Keywords AI-based models, tourism demand, tourism flow, geopolitical risk.

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INTRODUCTION

Geopolitical risk (GPR), usually defined as the uncertainty caused by armed conflicts, terrorist activities, and interstate political tensions that disrupt the stability of international relations, is increasingly seen as an important factor affecting the dynamics of global economic development (Sun et al., 2026). In the field of international tourism, this type of risk is of particular importance, since tourist flows are extremely sensitive to changes in the security, political, and information environment. An increase in the level of geopolitical instability can significantly change consumer behavior, influence the choice of travel destinations, and lead to a redistribution of international tourism demand.

The contemporary global environment is characterized by several major geopolitical challenges that directly or indirectly influence the development of international tourism. Among the most significant is the ongoing war between Russia and Ukraine, which has generated profound security concerns in Europe and substantially affected the attractiveness and accessibility of several destinations in the region. At the same time, increasing geopolitical tensions and military activities within the broader Middle Eastern geopolitical landscape, involving actors such as the United States, Israel, Iran, the United Arab Emirates, and Qatar, contribute to additional layers of uncertainty within the global tourism system. Potential zones of geopolitical tension may also emerge in other regions, including the Western Balkans, where political rhetoric and historical disputes periodically intensify regional instability.

Such geopolitical processes typically lead to a reduction in tourism demand in countries directly involved in conflicts. At the same time, their impact is not limited to these territories: geographically close states often experience an indirect effect due to the perception of increased security risks by potential tourists (Papagianni et al., 2023). In modern conditions, this is especially true for the countries of the Middle East, North Africa, and part of the Mediterranean region, in particular, such popular tourist destinations as Egypt, Tunisia, parts of Turkey, etc. As a result, a process of redistribution of international tourist flows is formed when demand shifts to alternative, perceived safer destinations.

While tourism demand decreases significantly in conflict-affected destinations, empirical evidence suggests that the impact of geopolitical risk is heterogeneous across countries. Some destinations experience substantial declines in tourist arrivals, while others demonstrate relative resilience depending on their attractiveness and perceived safety (Balli et al., 2019).

Moreover, geopolitical risk shocks have been shown to exert a significant and persistent negative effect on tourism demand (Hailemariam & Ivanovski, 2021; Papagianni et al., 2023), with both short-term disruptions and longer-term implications for tourist flows (Tiwari et al., 2019). These findings suggest that geopolitical instability does not simply reduce global tourism demand, but may also lead to a reallocation of tourist flows across destinations, as travelers adjust their choices in response to perceived risk.

In addition to the direct reduction in tourist flows and their spatial redistribution, geopolitical instability can form another important phenomenon—the so-called pent-up demand (Kostynets et al., 2020). In situations of increased risk, potential tourists often do not refuse to travel completely but only postpone their travel until the level of uncertainty decreases or the security environment stabilizes. As a result, demand does not disappear but accumulates over a period of time, which can lead to a sharp recovery in tourism activity after the end of crisis events or a decrease in geopolitical tensions. Such a time-shifted response of demand creates additional challenges for forecasting tourism flows, as traditional econometric models may face limitations in capturing complex behavioral and nonlinear aspects of pent-up demand dynamics under conditions of heightened geopolitical uncertainty.

In terms of the literature review, it should be noted that tourism is widely recognized as one of the economic sectors most sensitive to external shocks, particularly geopolitical instability, armed conflicts, and political crises. Numerous studies have shown that geopolitical risk significantly affects tourism flows by altering travelers' perceptions of safety and increasing uncertainty regarding travel decisions. For example, A. Blake and M.T. Sinclair demonstrated that political instability and security concerns can lead to substantial declines in international tourist arrivals due to risk perception and destination substitution behavior (Blake & Sinclair, 2003). Besides, recent empirical research further confirms that geopolitical shocks exert both immediate and persistent effects on tourism demand. Using a Bayesian heterogeneous panel vector autoregressive model, E. Papagianni et al. found that increases in geopolitical risk significantly reduce tourist arrivals across multiple emerging economies, with effects that can persist over time due to changes in destination attractiveness and perceived security conditions (Papagianni et al., 2023). Similarly, A.K. Tiwari et al. showed that tourism demand tends to be more sensitive to geopolitical risk than to economic policy uncertainty, emphasizing the long-term implications of geopolitical tensions for the tourism sector (Tiwari et al., 2019). Recent research in tourism economics also highlights the importance of multidimensional country risk factors. For instance, a study using a mixed-frequency global vector autoregressive model demonstrated that various country risks – such as financial, political, and institutional risks – can generate spillover effects across tourism markets due to economic and cultural linkages between destinations (Wang et al., 2026). Overall, these findings indicate that geopolitical instability not only directly affects tourism demand in conflict zones but can also influence tourism flows in neighboring regions through perceived regional risk.

The tourism sector has historically been affected by various crises, including wars, terrorism, financial crises, and pandemics. These events often lead to sudden contractions in tourism demand followed by gradual recovery phases. For example, global tourism experienced an unprecedented decline during the COVID-19 pandemic, when international tourist arrivals dropped by up to 80% in 2020 due to travel restrictions and safety concerns (UN Tourism). Research on tourism resilience suggests that crises often lead to behavioral changes among travelers, including postponement of travel plans, shifts to domestic tourism, or substitution toward safer destinations. Such dynamics frequently result in the redistribution of tourism flows between regions. Furthermore, studies on tourism recovery processes emphasize the phenomenon of pent-up demand (Kostynets et al., 2020), whereby tourism demand accumulates during crisis periods and subsequently materializes once travel conditions improve. This delayed behavioral response complicates forecasting efforts because traditional models often assume immediate demand adjustments rather than temporally lagged reactions.

Accurate forecasting of tourism demand plays a critical role in tourism planning, destination management, and policy development. Traditionally, tourism demand forecasting relied on time-series models and econometric approaches such as ARIMA, vector autoregression, and econometric regression models. These methods remain widely used due to their interpretability and strong theoretical foundations (Yi et al., 2025). However, the increasing availability of high-frequency data, such as search engine queries and social media activity, has created new opportunities for improving tourism demand prediction.

Despite the growing scholarly interest in tourism resilience and crisis impacts, existing research has largely focused on analyzing individual crisis events or assessing the short-term effects of political instability on specific destinations. Considerably less attention has been devoted to integrating geopolitical risk indicators into global tourism demand forecasting frameworks. Traditional econometric approaches may face challenges in capturing highly complex nonlinear interactions and high-dimensional relationships, particularly under conditions of rapidly changing geopolitical uncertainty. In this regard, artificial intelligence (AI) and machine learning techniques offer promising opportunities for analyzing large-scale datasets and identifying hidden patterns that may significantly improve forecasting accuracy under conditions of heightened uncertainty.

In recent years, artificial intelligence (AI) and machine learning techniques have emerged as promising tools for modeling tourism demand due to their ability to capture complex nonlinear relationships and process large datasets (Wang et al., 2025). AI techniques applied in tourism demand forecasting include artificial neural networks, random forests, support vector machines, and deep learning models. These methods have demonstrated higher predictive accuracy compared with traditional econometric approaches in many forecasting contexts (Henriques & Nobre Pereirsa, 2024). More recent studies have introduced advanced deep learning architectures, including transformer-based models designed to capture long-term dependencies in tourism time series data (Yi et al., 2025).

Despite the growing body of literature on tourism demand forecasting and the increasing recognition of geopolitical risk as a key determinant of global economic dynamics, significant gaps remain in the integration of these research streams. Existing studies provide strong evidence that geopolitical instability negatively affects tourism demand. For example, empirical analyses using panel models demonstrate that increases in geopolitical risk lead to persistent declines in tourist arrivals and represent a major driver of tourism fluctuations across countries (Papagianni et al., 2023). At the same time, widely used measures such as the Geopolitical Risk Index (GPR) and related macro-level indicators are not specifically designed for tourism systems. These indices primarily capture general geopolitical tensions but do not account for tourism-specific factors such as destination dependence on tourism or spatial proximity to conflict zones. Furthermore, existing studies show that the impact of geopolitical risk on tourism is heterogeneous across countries, suggesting the need for more context-specific measures of vulnerability (Balli et al., 2019).

In parallel, tourism demand forecasting has increasingly incorporated advanced data sources and machine learning techniques. Recent studies demonstrate that deep learning and artificial neural networks significantly improve forecasting accuracy compared to traditional econometric models (Tuncsiper, 2025). Moreover, the integration of search engine data, such as Google Trends, has been shown to enhance the predictive performance of tourism demand models by capturing real-time changes in travel interest and behavior (Nie et al., 2024).

However, despite these advancements, relatively few studies integrate geopolitical risk indicators into AI-based tourism forecasting frameworks. As a result, existing approaches may provide only a limited account of the complex nonlinear relationships among geopolitical instability, risk perception, and tourism mobility. In particular, limited attention has been given to the patterns through which geopolitical shocks may be associated with the redistribution of tourism flows across destinations and the emergence of pent-up demand effects (Kostynets et al., 2020). Therefore, there is a clear need for an integrated methodological approach that combines (i) a tourism-specific measure of geopolitical risk, (ii) behavioral and real-time indicators of tourist perception, and (iii) machine-learning techniques capable of modelling nonlinear dynamics. This study addresses this gap by developing a composite Geopolitical Tourism Risk Index (GTRI) and integrating it into an AI-based forecasting framework, thereby providing an analytical basis for examining how geopolitical instability may reshape global tourism demand, contribute to the redistribution of tourist flows, and generate or intensify pent-up demand effects.

Against this background, this study aims to introduce an AI-based framework for assessing the impact of geopolitical risk on global tourism demand under conditions of geopolitical instability. The study explorers the relationship between geopolitical risk and international tourism flows and demonstrates the analytical feasibility of incorporating geopolitical risk indicators into an AI-supported framework for tourism-demand analysis.

The main contributions of this research are threefold. First, the study introduces a conceptual framework for integrating geopolitical risk indicators into tourism demand analysis. The proposed framework combines a tourism-specific geopolitical risk indicator (GTRI) with a machine-learning modelling approach capable of integrating heterogeneous explanatory variables into a unified analytical structure for tourism-demand assessment. Second, it incorporates XGBoost as an AI-based analytical tool for capturing complex nonlinear relationships and interactions among heterogeneous geopolitical, economic, spatial, and behavioral determinants of tourism mobility. Third, the illustrative application identifies patterns that may be associated with tourism-flow redistribution and delayed demand responses under geopolitical uncertainty, providing a basis for further empirical investigation and potential practical interpretation.

The paper is structured as follows. Section 2 presents the methodological framework, including the construction of the GTRI and the AI-based forecasting model. Section 3 discusses the empirical results and scenario analysis. The final section concludes and outlines implications and directions for future research.

1. METHODOLOGY

1.1 Research design and analytical framework

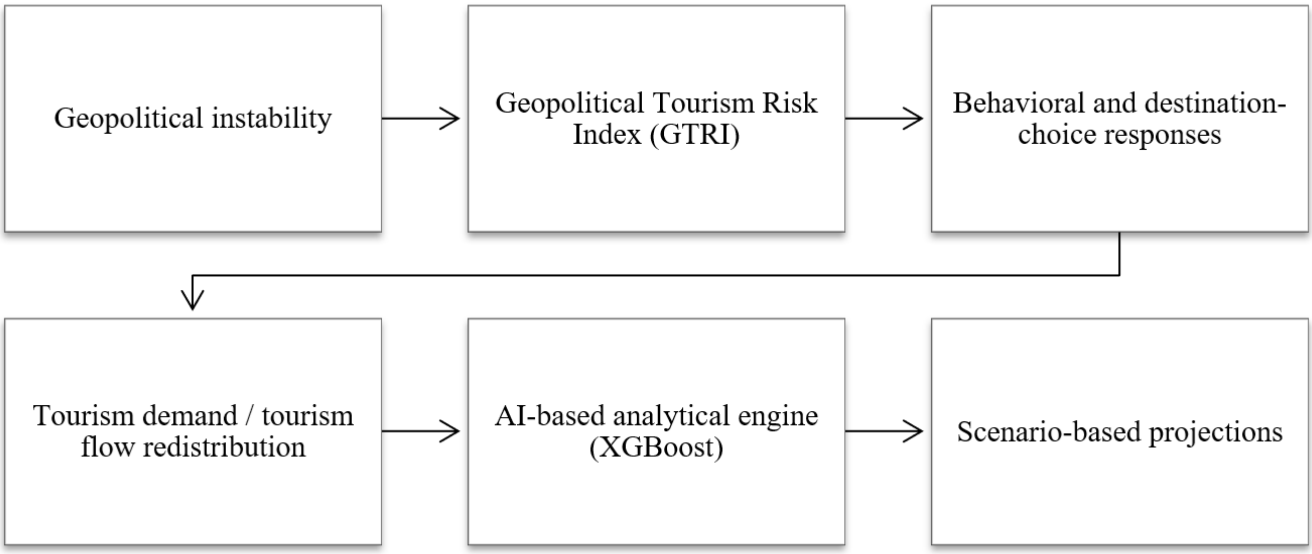
In this study, the AI-based framework is understood as an integrated methodological architecture comprising four interrelated elements: (i) heterogeneous geopolitical, economic, spatial, tourism-related, and behavioral inputs; (ii) the tourism-specific Geopolitical Tourism Risk Index (GTRI); (iii) XGBoost as the machine-learning analytical engine; and (iv) the interpretation of tourism-demand responses under alternative geopolitical-risk conditions.

To clarify the analytical logic of the study, Figure 1 presents the conceptual framework linking geopolitical instability with tourism demand forecasting. The framework assumes that geopolitical shocks shape destination risk through the Geopolitical Tourism Risk Index (GTRI), affect travel perception and destination choice, and consequently alter tourism demand and the redistribution of tourist flows. These changes are further incorporated into an AI-based forecasting model, which is used to generate scenario-based projections.

The proposed framework integrates traditional tourism indicators with alternative data sources that reflect real-time changes in tourist interest and geopolitical risk. In particular, the model incorporates macroeconomic indicators, a composite Geopolitical Tourism Risk Index (GTRI), and online search behavior derived from Google Trends. The inclusion of digital behavioral data allows the analysis to capture early signals of shifts in tourism demand that often precede actual travel flows.

The GTRI is constructed as a composite index that combines four normalized components: geopolitical risk, proximity to conflict zones, tourism dependence, and online risk perception. The index provides a quantitative measure of the exposure of tourism destinations to geopolitical instability and serves as a key explanatory variable in the forecasting model. While several global indices and travel risk maps exist, such as the Global Peace Index and various travel safety rankings, these measures are not specifically designed to capture the multidimensional nature of geopolitical risk in tourism systems. Existing tools primarily focus on general safety, conflict intensity, or crime levels, and do not explicitly account for tourism dependency, destination choice behavior, or real-time changes in risk perception. In contrast, the Geopolitical Tourism Risk Index (GTRI) proposed in this study integrates geopolitical, economic, spatial, and behavioral dimensions, providing a tourism-specific measure of risk that can be directly incorporated into forecasting models.

Figure 1: **Conceptual framework of AI-based tourism demand forecasting under geopolitical instability**



Source: built by authors

Figure 1 illustrates the overall analytical architecture of the proposed framework. The methodological framework consists of three main stages. First, a retrospective analysis of global tourism demand and major geopolitical shocks is conducted to identify structural changes in international tourism flows. Second, the tourism-specific Geopolitical Tourism Risk Index (GTRI) is constructed by integrating geopolitical, spatial, economic, and behavioral indicators of destination exposure and vulnerability. Third, the Extreme Gradient Boosting (XGBoost) algorithm is employed as the AI-based analytical tool of the framework to jointly process the GTRI, tourism-demand indicators, and other heterogeneous explanatory variables, and to explore nonlinear relationships and interaction effects without requiring their functional forms to be specified in advance. The resulting analytical outputs are subsequently used for the exploratory interpretation of tourism-flow redistribution, pent-up demand effects, and alternative geopolitical-risk scenarios.

1.2 Data sources and variables

The empirical analysis combines data from several international sources. International tourism arrivals were obtained from UN Tourism (UN Tourism, 2025), macroeconomic indicators from the World Bank Country Profile (World Bank, 2025), geopolitical risk data from the Geopolitical Risk Index database developed by Caldara and Iacoviello (2022), crude oil prices from the U.S. Energy Information Administration (EIA, 2025), and behavioral indicators from Google Trends. The study covers the period 2004–2024 for major international tourism destinations.

The empirical dataset includes selected tourism destinations from the Eastern Mediterranean and Middle East regions over the period 2014–2024. The dataset combines annual observations on tourism demand, macroeconomic indicators, geopolitical risk measures, and online behavioral indicators. Due to data availability constraints and the exploratory nature of the study, the analysis is based on a limited and partially unbalanced sample. Table 1 summarizes the variables, definitions, and data sources used in the empirical analysis.

Table 1: **Variables and data sources***

Variable	Operational definition	Source
TD	International tourist arrivals	UN Tourism; World Bank
GDP	Gross domestic product (USD billion, 2019)	World Bank – WITS Country Profile
OIL	Global crude oil prices	World Bank Commodity Markets Database
GPR	Geopolitical Risk Index	Caldara and Iacoviello
ORP	Online Risk Perception proxy derived from Google Trends travel-safety search intensity (0–100)	Google Trends
PROX	Proximity to major geopolitical conflict zones (authors' ordinal assessment)	Authors' assessment
TDP	Tourism dependence measured as tourism receipts divided by GDP	Authors' calculation using World Bank/ WITS and tourism receipts data
GTRI	Composite Geopolitical Tourism Risk Index combining GPR, PROX, TDP and ORP	Authors' calculations

* **Notes:** GPR was normalized using a control value of 200. ORP was normalized to a 0–1 scale by dividing Google Trends scores by 100. Tourism dependence (TDP) was calculated as the ratio of tourism receipts to GDP. The GTRI was computed as a weighted composite index with equal weights assigned to GPR, PROX, TDP, and ORP.

The presented GTRI values should be interpreted as illustrative estimates within the proposed framework rather than as definitive geopolitical risk rankings. Differences across destinations may also reflect the influence of behavioral and perception-based indicators incorporated into the index.

The dependent variable is tourism demand, proxied by international tourist arrivals. Independent variables include gross domestic product (GDP), oil prices, and online search intensity derived from Google Trends, which captures tourist interest in travel-related queries. Additionally, a composite Geopolitical Tourism Risk Index (GTRI) is constructed to quantify the exposure of tourism destinations to geopolitical instability. Unlike existing geopolitical and safety indices, the proposed GTRI is specifically designed to capture tourism system vulnerability by integrating geopolitical risk, destination proximity, economic exposure, and behavioral response indicators.

1.3 Construction of the Geopolitical Tourism Risk Index (GTRI)

To quantify the impact of geopolitical instability on tourism systems, this study offers a composite Geopolitical Tourism Risk Index (GTRI). The construction of the GTRI is based on the assumption that the effect of geopolitical instability on tourism cannot be adequately represented by a single general geopolitical-risk indicator. Tourism-related exposure arises through several complementary channels. First, geopolitical risk reflects the intensity of adverse political and security events. Second, spatial proximity captures the possibility of regional spillover effects, whereby destinations located near conflict zones may be perceived as unsafe even when they are not directly involved. Third, tourism dependence reflects the structural vulnerability of national economies whose revenues and employment are highly reliant on international tourism. Fourth, online risk perception captures the behavioral response of potential tourists to security-related information. Taken together, these dimensions allow the GTRI to combine objective exposure, structural vulnerability, and perceived risk within a tourism-specific analytical framework. The index integrates four dimensions that capture both objective and perceived aspects of geopolitical risk:

1. **Geopolitical risk (GPR)** – reflecting the overall level of geopolitical tensions and conflict intensity (Caldara & Iacoviello, 2022). The concept of geopolitical risk measurement builds upon the Geopolitical Risk Index (GPR) developed by Caldara and Iacoviello (2022), which quantifies geopolitical tensions using a news-based approach derived from newspaper coverage of adverse geopolitical events. Recent studies have demonstrated that geopolitical risk has a persistent negative effect on tourism demand and constitutes a major driver of tourism fluctuations across countries (Papagianni et al., 2023). Recent advancements extend traditional geopolitical risk measurement by incorporating artificial intelligence techniques to improve the precision of risk identification and classification (Iacoviello & Tong, 2026).
2. **Proximity to conflict zones (PROX)** – measuring the geographical and regional closeness of a destination to areas affected by geopolitical instability. PROX is operationalized as a categorical indicator reflecting the geographical proximity of a destination to regions affected by major geopolitical instability and armed conflict. PROX was operationalized as an ordinal indicator reflecting the geographical proximity of each destination to major geopolitical conflict zones, based on a predefined expert classification.
3. **Tourism dependence (TDP)** – representing the relative importance of tourism in the national economy, calculated as the share of tourism receipts in GDP. Tourism dependence (TDP) is calculated based on pre-pandemic data (2019), which represents the last period of stable tourism activity before the COVID-19 shock. The use of 2019 data allow for a consistent measurement of structural dependence on tourism, avoiding distortions associated with the pandemic period. Unlike short-term indicators such as geopolitical risk or online search behavior, tourism dependence is treated as a structural variable that changes gradually over time. Therefore, it is assumed to remain relatively stable in the short run and can be combined with more recent indicators within the composite index. Similar approaches are widely used in tourism and macroeconomic studies, where structural indicators are combined with high-frequency variables.
4. **Online risk perception (ORP)** – capturing tourists' perceived risk based on search intensity for safety-related travel queries obtained from Google Trends. The ORP indicator represents destination-specific online risk perception derived from Google Trends search intensity related to travel-safety queries. It is used as a proxy for tourists' perceived security concerns and normalized to ensure comparability across destinations. Online risk perception (ORP) is measured using Google Trends data based on search queries related to travel safety (e.g., "is it safe to travel to [destination]"). While the GPR component reflects broader geopolitical event intensity at the macro level, ORP is intended to capture tourism-specific behavioral responses and perceived travel safety reflected in online search activity. These indicators capture real-time changes in perceived travel risk and serve as a proxy for tourists' behavioral responses to geopolitical instability. Google Trends indicators were collected using normalized search intensity for travel safety-related queries and aggregated at the annual level to ensure comparability across destinations and time periods. Because destination-specific Google Trends datasets are not uniformly available across all countries, ORP was operationalized as a best-available proxy reflecting destination-specific travel-safety search salience. This indicator should therefore be interpreted as an approximate measure of online risk perception.

All variables are normalized using min-max scaling to ensure comparability across dimensions:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

The composite index is calculated as a weighted sum of the normalized components:

$$GTRI = w_1 \cdot GPR + w_2 \cdot PROX + w_3 \cdot TDP + w_4 \cdot ORP$$

The four components were normalized prior to aggregation to ensure comparability despite differences in measurement scales. Given the absence of a priori theoretical justification for assigning unequal importance to specific components, equal weights are applied (i.e.,). Equal weighting was selected to preserve interpretability and to avoid imposing subjective assumptions regarding the relative importance of individual dimensions within an exploratory composite-index framework. The resulting index takes values in the range [0,1], where higher values indicate greater exposure of a destination to geopolitical tourism risk.

The novelty of the proposed GTRI lies in its ability to capture not only the level of geopolitical instability, but also its transmission into tourism systems through spatial proximity, economic exposure, and behavioral responses, and its integration into an AI-based forecasting framework.

1.4 AI forecasting model (XGBoost)

To capture complex nonlinear relationships between geopolitical instability and tourism demand, this study applies an approach based on the Extreme Gradient Boosting (XGBoost) algorithm. Within the proposed analytical framework, XGBoost functions as the analytical engine for jointly processing heterogeneous geopolitical, economic, spatial, and behavioral indicators integrated through the GTRI. XGBoost was selected not because the study seeks to establish its universal superiority over econometric methods, but because it provides a flexible environment for jointly processing heterogeneous predictors, nonlinear relationships, and interaction effects. At the same time, its use involves recognized limitations, including sensitivity to sample size, hyperparameter selection, and the risk of overfitting. For this reason, the present implementation is treated as an illustrative analytical application rather than as a comprehensive validation of the algorithm. XGBoost serves as the analytical engine of the proposed framework.

The model specification can be expressed as:

$$TD_{it} = f(GDP_{it}, OIL_t, GTRI_{it}, GT_{it})$$

where:

- denotes tourism demand for country at time ,
- represents economic activity,
- captures global oil price dynamics,
- reflects geopolitical tourism risk,
- denotes Google Trends indicators of tourism interest.

The dataset is divided into training and testing subsets using a standard train-test split procedure. Model performance is evaluated using three widely applied metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The dataset was divided chronologically into training and testing subsets in order to preserve the temporal structure of the observations.

To assess the added value of the AI-based approach, the performance of the XGBoost model is compared with a baseline linear regression model. This comparison allows for evaluating whether incorporating nonlinear relationships and geopolitical risk indicators improves forecasting accuracy.

Due to the exploratory scope of the study, the model was implemented using standard parameter settings without extensive hyperparameter optimization.

Within the proposed framework, tourism-flow redistribution is interpreted through differences in the estimated responses of destinations characterized by different levels of geopolitical exposure and GTRI values. Pent-up demand effects are interpreted as delayed increases in tourism demand following periods of elevated geopolitical risk, consistent with the conceptual understanding developed by Kostynets et al. (2020). These phenomena are not introduced as directly observed variables but as analytical interpretations derived from the relationships identified within the framework.

1.5 Scenario analysis

In order to assess the sensitivity of tourism demand to geopolitical instability, scenario analysis is conducted based on variations in the GTRI. Three scenarios are considered:

- **Baseline scenario** – reflecting average observed conditions;
- **Escalation scenario** – assuming an increase in geopolitical risk (e.g., +20% in GTRI);
- **Stabilization scenario** – assuming a reduction in geopolitical tensions (e.g., −20% in GTRI).

Predicted tourism demand under each scenario is generated using the trained XGBoost model.

1.6 Identification of redistribution and pent-up demand effects

The methodological framework also enables the identification of structural changes in tourism flows. Redistribution effects are analyzed by comparing predicted demand across destinations with different levels of GTRI. Destinations with higher risk are expected to experience demand declines, while relatively safer destinations may benefit from substitution effects.

Pent-up demand is captured through the inclusion of Google Trends indicators, which serve as leading signals of tourism interest prior to actual travel decisions. This allows the model to account for temporal lags between intention and realized tourism demand. The proposed framework is intended to identify analytical patterns associated with tourism-flow redistribution and pent-up demand rather than to establish causal estimates of these phenomena.

2. RESULTS

2.1 Contextual background on geopolitical shocks and tourism demand

The first stage of the empirical analysis examines the dynamics of global tourism demand in the context of major geopolitical shocks in recent years. The purpose of this analysis is to identify structural changes in international tourism flows and to assess the sensitivity of tourism demand to geopolitical instability.

2.2 Geopolitical Tourism Risk Index (GTRI) results

The second stage of the analysis focuses on the construction and empirical assessment of the Geopolitical Tourism Risk Index (GTRI), which is designed to quantify the exposure of tourism destinations to geopolitical instability.

The calculated GTRI values reveal substantial cross-country differences in the level of geopolitical tourism risk. The index effectively captures both direct exposure to geopolitical tensions and indirect effects related to regional proximity, economic dependence on tourism, and perceived risk among potential travelers. Table 2 presents the estimated GTRI values for selected tourism destinations.

Table 2: **Geopolitical Tourism Risk Index (GTRI) across selected destinations**

Destination	GTRI	Risk level	Notes
Israel	0,67	High	Direct conflict exposure; ORP kept very high.
Egypt	0,52	Medium-High	Regional spillover exposure plus tourism dependence.
Turkey	0,46	Medium	Regional spillover exposure; medium ORP proxy.
United Arab Emirates	0,47	Medium	Regional exposure offset by destination resilience.
Qatar	0,45	Medium	Regional exposure; moderate ORP proxy.
Cyprus	0,40	Medium-Low	Close to conflict region but lower ORP than Eastern hotspots.
Greece	0,36	Low	Lower proximity and lower ORP proxy.

Source: built by authors using uploaded GPR data, World Bank/WITS GDP references, tourism receipts series, and provisional ORP proxy.

Table 2 presents average illustrative GTRI values calculated over the observation period.
The results indicate that destinations directly affected by geopolitical conflicts, such as Israel, exhibit the highest levels of tourism-related risk. In contrast, relatively stable destinations such as Greece demonstrate significantly lower exposure.
At the same time, several countries occupy an intermediate position. For instance, Turkey, the United Arab Emirates, and Qatar are not directly involved in major conflicts but remain exposed to regional geopolitical dynamics. Their GTRI values reflect a combination of proximity to conflict zones and high integration into global tourism networks.

Importantly, the index does not simply reflect the presence or absence of conflict but captures a multidimensional structure of tourism risk. The inclusion of tourism dependence and online risk perception allows the GTRI to account for both structural vulnerability and behavioral responses of tourists. The results confirm that geopolitical risk in tourism is not binary but exists along a continuum. This enables the classification of destinations into risk categories (high, medium, and low), which is essential for comparative analysis and forecasting.

Moreover, the GTRI provides a consistent metric that can be directly incorporated into econometric and machine learning models. In particular, it serves as a key explanatory variable in the AI-based forecasting framework developed in this study.
Overall, the empirical results demonstrate that the GTRI is a valid and informative measure of geopolitical tourism risk, capturing both objective exposure and perceived risk, and providing a robust basis for subsequent modeling of tourism demand.

2.3 AI-based forecasting results (XGBoost)

The third stage of the analysis focuses on the application of an artificial intelligence approach to model the relationship between geopolitical instability and tourism demand.

Given the exploratory nature of the study and data availability constraints, the XGBoost implementation should be interpreted primarily as an illustrative proof-of-concept application rather than as a fully optimized production forecasting model.
To capture complex nonlinear relationships between geopolitical risk and tourism demand, this study employs the Extreme Gradient Boosting (XGBoost) algorithm. The model integrates macroeconomic variables, the Geopolitical Tourism Risk Index (GTRI), and behavioral indicators derived from Google Trends, following the specification:

$$TD_{it} = f(GDP_{it}, OIL_t, GTRI_{it}, GT_{it})$$

where tourism demand depends on economic conditions, energy prices, geopolitical risk, and online search behavior.

Given data availability constraints and the exploratory nature of the study, the model is implemented on a constructed dataset that combines available macroeconomic indicators, tourism statistics, and proxy measures of geopolitical risk and behavioral responses. This approach allows for demonstrating the analytical potential of the proposed framework and its applicability to tourism demand forecasting under geopolitical instability.

The dataset is divided into training and testing subsets using a standard train–test split procedure. Model performance is evaluated using widely applied metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). To assess the added value of the AI-based approach, the XGBoost model is compared with a baseline linear regression model. The illustrative XGBoost implementation demonstrates the feasibility of incorporating the GTRI and heterogeneous explanatory indicators into a unified machine-learning environment, reflecting its ability to capture nonlinear relationships and interaction effects between geopolitical risk and tourism demand. The application illustrates how nonlinear associations and interaction effects may be explored within the proposed framework.

The analysis highlights the importance of geopolitical risk in shaping tourism demand within the proposed framework. The GTRI serves as a composite indicator of tourism-related geopolitical exposure and provides a consistent measure that can be incorporated into AI-based tourism demand models. This interpretation is consistent with the cross-country variation observed in Table 2, where destinations with higher GTRI values exhibit greater levels of tourism-related geopolitical risk than relatively stable destinations. The illustrative application further suggests that higher GTRI values are generally associated with lower tourism demand, whereas lower-risk destinations tend to demonstrate comparatively stronger demand patterns. Behavioral indicators derived from Google Trends complement the framework by reflecting changes in online information-seeking behavior that may precede travel decisions, supporting the inclusion of digital behavioral data in tourism demand analysis.

The application of the XGBoost model allows for capturing nonlinear relationships between geopolitical instability and tourism demand. The results suggest that the impact of geopolitical risk is not proportional across different levels of exposure. At relatively low levels of risk, tourism demand remains stable and may become more pronounced under elevated geopolitical risk conditions. Furthermore, the interaction between geopolitical risk and behavioral indicators amplifies these effects. Changes in online search activity reflect shifts in tourist preferences and contribute to the dynamic adjustment of tourism demand across destinations.

Overall, the illustrative application of the XGBoost model demonstrates the feasibility of integrating heterogeneous geopolitical, economic, spatial, and behavioral indicators within a unified AI-supported analytical framework. The integration of the GTRI into the model framework enhances its explanatory power and allows for capturing complex relationships that are not adequately represented in linear models. The results highlight the importance of combining structural indicators of risk with real-time behavioral data in order to better understand and anticipate changes in tourism demand. These findings provide a methodological foundation for future empirical applications based on more extensive datasets and confirm the relevance of artificial intelligence as a tool for analyzing tourism dynamics in uncertain global environments. The following interpretation is based on the analytical relationships identified by the proposed framework rather than on the direct estimation of separate redistribution or pent-up-demand equations.

2.4 Tourism flow redistribution and pent-up demand

The final stage of the analysis focuses on the interpretation of analytical patterns associated with tourism-flow redistribution and pent-up demand effects identified within the proposed framework.

Table 3: **Redistribution of tourism demand across destinations**

Destination	GTRI	Observed effect on demand
Israel	0.67	Significant decline
Egypt	0.52	Moderate decline
Turkey	0.46	Mixed / reallocated flows
United Arab Emirates	0.47	Stable / partially resilient
Qatar	0.45	Stable
Cyprus	0.40	Moderate increase
Greece	0.36	Increase

Source: calculated by authors

The reported effects represent qualitative interpretations derived from the exploratory analytical framework and scenario-based assessment rather than direct quantitative forecasts. The results indicate that geopolitical instability does not lead to a uniform decline in global tourism demand. Instead, it generates a process of spatial redistribution, whereby tourist flows shift from high-risk to lower-risk destinations. This pattern is consistent with the variation in GTRI values identified destinations with higher GTRI scores, such as Israel (0.67) and Egypt (0.52), experience stronger negative impacts on tourism demand, while countries with lower GTRI values, such as Greece (0.36) and Cyprus (0.40), demonstrate greater resilience and, in some cases, relative gains in tourist inflows. Intermediate-risk destinations, including Turkey (0.46), the United Arab Emirates (0.47), and Qatar (0.45), occupy a transitional position. Their performance reflects a balance between exposure to regional instability and their ability to remain attractive as alternative destinations.

These results suggest the presence of a substitution effect in tourism demand. Rather than abandoning travel altogether, tourists tend to reallocate their travel plans toward destinations perceived as safer. This behavior leads to a redistribution of tourism flows across regions rather than a uniform contraction of demand.
Importantly, the redistribution effect is not purely geographical but is also influenced by perceived risk, accessibility, and destination competitiveness. As a result, even geographically proximate destinations may experience different outcomes depending on their relative GTRI values.

In addition to spatial redistribution, the analysis reveals the presence of pent-up demand effects. Tourism demand does not respond instantaneously to geopolitical shocks but evolves over time as travelers adjust their perceptions and decisions. The inclusion of Google Trends data provides valuable insights into these behavioral dynamics. Changes in online search activity related to travel safety and destination interest often precede actual changes in tourist arrivals, indicating that search behavior serves as an early signal of demand shifts.

The results show that increases in GTRI are associated with a rise in safety-related search queries, reflecting heightened risk perception among potential travelers. However, actual travel decisions are adjusted with a time lag, as tourists reconsider their options and redirect their travel plans. This lagged adjustment mechanism helps explain why tourism demand does not collapse immediately following geopolitical shocks but instead undergoes a gradual reconfiguration.

Taken together, the results highlight two key mechanisms through which geopolitical instability affects tourism:

1. **Redistribution effect** – tourism flows shift from high-risk to lower-risk destinations;
2. **Pent-up demand effect** – changes in tourist behavior occur gradually, mediated by evolving risk perceptions.

These mechanisms are captured by the combined use of the GTRI and behavioral indicators within the AI-based forecasting model. While the GTRI reflects structural and geopolitical exposure, Google Trends data capture real-time changes in perception and decision-making.

Overall, the findings demonstrate that geopolitical instability reshapes tourism systems not only by reducing demand in affected regions, but also by redistributing tourist flows and introducing temporal delays in travel behavior. These dynamics are essential for understanding and forecasting tourism demand in an increasingly uncertain global environment.

2.5 Exploratory scenario analysis of tourism demand

The final stage of the analysis applies the proposed AI-based framework to generate scenario-based projections of tourism demand under different levels of geopolitical instability.

To assess the potential impact of changing geopolitical conditions, three alternative scenarios are considered:

- **Baseline scenario**, reflecting current levels of geopolitical risk;
- **Escalation scenario**, assuming an increase in geopolitical instability;
- **Stabilization scenario**, assuming a reduction in geopolitical tensions.

The presented scenarios are intended as qualitative and illustrative interpretations of potential tourism-demand responses under alternative geopolitical-risk conditions rather than as precise quantitative forecasts.

The baseline scenario represents the current configuration of geopolitical risk as reflected in the GTRI values presented above. Under this scenario, tourism demand remains differentiated across destinations according to their relative exposure to geopolitical instability. High-risk destinations continue to experience lower levels of demand, while low-risk destinations maintain relatively stable or increasing tourist inflows. Intermediate destinations exhibit mixed performance, reflecting both risk exposure and substitution dynamics. The escalation scenario assumes an increase in geopolitical risk, reflected in higher GTRI values across destinations. Under this scenario, tourism demand is expected to decline in high-risk and medium-risk destinations, with stronger negative effects observed in regions directly affected by geopolitical tensions. At the same time, the redistribution effect becomes more pronounced. Tourists are more likely to shift toward destinations perceived as safer, leading to increased demand in low-risk countries. However, the overall level of global tourism demand may also decline due to heightened uncertainty and reduced travel confidence.

The stabilization scenario assumes a reduction in geopolitical risk, reflected in lower GTRI values. Under this scenario, tourism demand is expected to recover, particularly in destinations previously affected by geopolitical instability. The results suggest that the recovery process may be gradual and influenced by pent-up demand effects. Improvements in perceived safety are reflected in online search behavior before translating into actual travel flows, indicating the importance of behavioral dynamics in the recovery of tourism demand. The comparison of scenarios highlights the sensitivity of tourism demand to changes in geopolitical risk and confirms the importance of incorporating such risk into forecasting models.

Across all scenarios, the results demonstrate that tourism demand responds asymmetrically to changes in geopolitical conditions. While increases in risk lead to rapid declines in demand, recovery under stabilization scenarios tends to be more gradual. Moreover, the scenario analysis reinforces the existence of redistribution and pent-up demand effects identified in previous sections. These mechanisms play a key role in shaping tourism dynamics under uncertainty and should be explicitly considered in policy and planning decisions.

CONCLUSION

The study should be interpreted as an initial conceptual framework as it introduces an AI-based framework for assessing international tourism demand under conditions of geopolitical instability. Its principal contribution lies in the construction of the tourism-specific Geopolitical Tourism Risk Index (GTRI) and its integration with heterogeneous tourism-demand indicators through an AI-supported analytical architecture. The framework combines geopolitical risk, spatial exposure, tourism dependence, macroeconomic indicators, and behavioral signals derived from online search activity. Within this architecture, XGBoost functions as an analytical tool for jointly processing multidimensional inputs and exploring nonlinear relationships and interaction effects.

The illustrative application indicates that geopolitical instability, as represented by the GTRI, is associated with differentiated tourism-demand patterns across the analyzed destinations. Higher GTRI values generally correspond to lower or less stable inbound tourism demand, whereas destinations with lower risk exposure tend to demonstrate comparatively more resilient demand patterns. The results also suggest that tourism responses to geopolitical instability may involve changes in destination choice, the redistribution of tourism flows, and delayed demand responses associated with evolving risk perceptions. These findings support the analytical relevance of combining structural risk indicators with behavioral data when examining tourism demand under uncertainty.

Several limitations should be acknowledged. First, the GTRI is based partly on proxy indicators and an equal-weighting scheme, which may affect the resulting risk estimates. Second, the empirical specification does not incorporate the full range of determinants commonly included in structural tourism-demand models, limiting the isolation of geopolitical-risk effects from other economic influences. Third, Google Trends indicators may reflect broader informational attention and expectations rather than direct tourism intentions. Fourth, the analysis covers a limited set of destinations and observation periods, which restricts the generalizability of the findings. Finally, the XGBoost implementation is illustrative and does not constitute comprehensive forecasting validation across alternative models and specifications.

Future research could address these limitations by refining the construction of geopolitical risk indices using alternative weighting approaches, extending the model to include a broader set of tourism demand determinants, and testing the framework across larger and more heterogeneous datasets. Additional work could also explore alternative machine learning methods and compare their performance under different data conditions.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors declare that generative AI and AI-assisted technologies were used in a limited capacity to support language editing and improve the clarity of the manuscript. These tools were not used to generate scientific content or to formulate the research design and conclusions. Artificial intelligence methods were employed solely as part of the research methodology, including the application of the XGBoost model for empirical analysis. In addition, some external data sources used in the study may incorporate AI-based techniques; however, these data were obtained from established sources and are appropriately cited. All methodological design, data processing, model implementation, and interpretation of results, including the development of the Geopolitical Tourism Risk Index (GTRI), were carried out by the authors. The authors take full responsibility for the content of this publication.

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