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Financial Resilience of Tourism-Dependent Economies under Global Uncertainty: A Panel Explainable Machine Learning Approach

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ABSTRACT

Purpose – Tourism-dependent economies are particularly exposed to persistent global uncertainty, yet tourism resilience and macro-financial resilience have largely been examined as separate phenomena. This study develops a Tourism Financial Resilience Index (TFRI) and investigates how tourism dependency, financial robustness, and global uncertainty are associated with tourism financial resilience across countries.

Design/methodology/approach – The study employs an unbalanced panel of 144 tourism-dependent countries over the 2010–2020 period, comprising 1,533 country-year observations. The Tourism Financial Resilience Index and Financial Robustness Index are constructed using Principal Component Analysis (PCA). Country fixed-effects estimation with Driscoll–Kraay robust standard errors is combined with Panel Quantile Regression to examine conditional-mean and distributional associations. Random Forest, XGBoost, and LightGBM models, interpreted using SHapley Additive exPlanations (SHAP), are further employed to explore nonlinear predictive patterns and model-based predictor importance.

Findings – Global uncertainty exhibits a negative and statistically significant association with Tourism Financial Resilience in the fixed-effects model and across all estimated conditional quantiles. Tourism dependency and financial robustness are not statistically significant in the baseline fixed-effects specification but become positive and significant across the 25th, 50th, and 75th quantiles, indicating that their relationships with resilience are specification-dependent. The interaction between global uncertainty and financial robustness is negative and significant in the fixed-effects model; however, its sign does not support the hypothesized buffering effect of financial robustness, and neither moderation effect is significant in the quantile regressions. The machine-learning models exhibit limited out-of-sample generalization, with negative test R^2 values, and are therefore interpreted primarily as complementary tools for examining nonlinear predictive structure. Within the LightGBM model, SHAP identifies global uncertainty as the most influential predictor, followed by GDP per capita and tourist-arrival intensity.

Discussion – The findings demonstrate that Tourism Financial Resilience is shaped by the interaction of tourism exposure, macro-financial conditions, and persistent global uncertainty rather than by tourism specialization alone. The study contributes to the tourism-resilience literature by integrating tourism and financial resilience within a multidimensional framework and by combining panel econometric inference with explainable machine learning while maintaining a clear distinction between statistical association, predictive performance, and model-based variable importance.

ETHICAL APPROVAL: This study uses publicly available secondary macroeconomic and financial data and does not involve human participants; therefore, ethics committee approval was not required.

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1. Introduction

The tourism industry has become one of the world's vital economic sectors, accounting for a significant share of gross domestic product (GDP), employment, foreign exchange income, investment, and regional growth. According to the United Nations World Tourism Organization (UN Tourism, 2025), international tourism has recovered significantly from the unprecedented interferences generated by the COVID-19 crisis, and international tourist arrivals are approaching or exceeding rates before the pandemic in a number of countries.

Recent global crises have revealed that as economic sectors, tourism is significantly more exposed to systemic shocks. Unlike manufacturing or agriculture, the demand for tourism responds instantly in times of uncertainty, as international travel activities are heavily influenced by consumer confidence, disposable income, transportation accessibility, exchange rate stability, and political security (Gössling et al., 2021). Thus, external shocks coming from financial markets are quickly transferred to tourism income, investment decision-making, employment, and business sustainability. The growing convergence between global financial markets and the activities of tourism indicates that the resilience of tourism can no longer be assessed only through visitor arrival or tourist receipts metrics. Rather, the financial resilience of economies that rely on tourism to absorb, adjust to, or recover from external shocks has become a fundamental issue of concern for both policymakers and researchers (OECD, 2026).

The increasing frequency of global uncertainty further strengthens the need to integrate these two research streams. Economic policy uncertainty, geopolitical tensions, climate transition risks, energy price volatility, and financial market instability simultaneously influence international travel demand and macroeconomic performance (Baker et al., 2016; Caldara & Iacoviello, 2022; Ahir et al., 2022). Nevertheless, existing empirical studies generally investigate these relationships separately, focusing either on tourism resilience or on macro-financial vulnerability, without proposing an integrated analytical framework capable of capturing their dynamic interactions.

Drawing on such theoretical and methodological voids, this research proposes the term Tourism Financial Resilience (TFR), and designs the Tourism Financial Resilience Index (TFRI) for tourism-dependent economies. In contrast to existing resilience measures that predominantly emphasize tourism performance or post-shock recovery, the proposed index combines tourism-performance indicators with broader dimensions of macroeconomic and socioeconomic stability, including real economic growth, price stability, and labour-market conditions.

Apart from providing the foundation for a comprehensive composite index, this study advances the literature on tourism resilience in three ways. First, it presents an integrative framework drawing on Dynamic Capabilities Theory, Complex Adaptive Systems Theory, and Financial Resilience Theory to explain the multidimensional nature of tourism financial resilience. Second, it proposes the Tourism Financial Resilience Index (TFRI), which extends existing tourism resilience measures by explicitly incorporating macro-financial stability alongside tourism performance. Third, the study combines robust panel econometric techniques with explainable machine-learning models, enabling robust statistical inference, the assessment of heterogeneous associations, and the exploration of nonlinear predictive patterns within a unified empirical framework. This hybrid approach jointly evaluates statistical associations, distributional heterogeneity, nonlinear predictive structure, and model interpretability, thereby providing complementary evidence on the determinants of tourism financial resilience.

The empirical analysis therefore combines panel-data econometrics and explainable machine learning as complementary rather than competing approaches. The econometric component evaluates within-country and distributional associations, whereas the machine-learning component examines nonlinear predictive structure and model-based variable importance. This combined design improves analytical breadth and interpretability without implying causal identification.

The rest of the paper is structured as follows. Section 2 has a literature review on tourism resilience, financial resilience, and global uncertainty. Section 3 develops the conceptual framework and research hypotheses. Section 4 includes the data, variable construction, and empirical methodology. Empirical results of panel econometric models and explainable machine learning analyses are included in Section 5. The final section presents the principal findings, policy implications, limitations, and directions for future research.

2. Literature Review

2.1 Tourism Financial Resilience under Global Uncertainty

In the last two decades, resilience has emerged as one of the leading theoretical paradigms within tourism research, largely due to the series of global crises experienced over the last 20 years. Resilience generally describes a system's ability to absorb disturbances, adapt to changing conditions, reorganize its internal structure and recover while preserving its essential functions, which derives from ecological and systems theory (Folke et al., 2010; Hall et al., 2022). In the world of tourism studies, it has slowly morphed, however, from just destination recovery after natural disasters, to an analysis of wider economic, institutional, environmental and organizational capacities that help tourism systems to remain functional under persistent uncertainty. As a result, contemporary resilience research not only comprehends tourism as an economic activity but as a complex adaptive system whose sustainability depends on the interplay of tourism demand, macroeconomic stability, quality of governance, financial resources, technological capability, and institutional flexibility.

Those vulnerabilities have been compounded by global uncertainty. The international landscape in the post-pandemic environment is one of ongoing inflation, tighter monetary policies, geopolitical conflicts, energy price volatility, climate-related disasters, and increasingly interconnected financial markets. These risks impact international mobility, investment choices, tourism expenditure, and macroeconomic performance at the same time. Economic policy uncertainty and geopolitical uncertainty, as such, have become significant determinants of tourism activity, as they shape demand-side behavior and destination-level investment decisions. Uncertainty cannot now be reduced to simply isolated exogenous disturbances; uncertainty has become rather a structural characteristic of the present-day global economy and thus the capacity for resilience frameworks that can integrate tourism performance with financial stability is required.

The increasing complexity of global risks has significantly changed the conceptual understanding of resilience. Previous studies mostly saw resilience as the speed with which tourism demand rebounded from natural disasters, epidemics, or political crises (Hall et al., 2018). Recent studies take a wider systems approach that acknowledges adaptive capacity, institutional quality, governance, financial flexibility, digital transformation, and sustainable development as key dimensions of resilience (UN Tourism, 2024; OECD, 2026). Yet, although these developments have advanced, empirical studies still use the largely focused tourism-specific data, such as international tourist arrivals, tourism receipts, occupancy rates, and tourism GDP. While these measures do fairly well to estimate the performance of tourism, they provide only limited insights into the underlying financial mechanisms that make it hard for tourism-based economies to remain able to achieve macroeconomic stability in an environment characterized by extended periods of uncertainty.

A key remaining limitation concerns measurement. Existing tourism resilience indicators predominantly capture tourism performance and destination recovery, while giving comparatively limited attention to the macro-financial capacity required to absorb persistent external shocks. This measurement gap motivates the development of a multidimensional indicator that jointly reflects tourism performance and macroeconomic resilience.

2.2 Explainable Machine Learning in Tourism Finance and Research Gap

The growing complexity of tourism systems has simultaneously changed methodological methodologies in the fields of tourism economics and finance. Conventional panel regression, generalized least squares, and fixed-effects estimators remain valuable for estimating average conditional associations. However, these approaches may be less suited to capturing nonlinearities, threshold effects, and higher-order interactions that can characterize tourism systems under persistent global uncertainty.

A further methodological challenge concerns model interpretability. Although ensemble learning algorithms frequently outperform traditional statistical models in predictive accuracy, they often operate as "black-box" systems that provide limited information regarding the contribution of individual explanatory variables. This limitation reduces their usefulness for public policy because policymakers require transparent evidence regarding the mechanisms through which specific economic, financial, or institutional factors influence resilience.

Explainable Artificial Intelligence (XAI) has emerged as an important solution to this challenge. Among existing explainability techniques, SHapley Additive exPlanations (SHAP) has become one of the most widely adopted approaches because it quantifies the marginal contribution of each explanatory variable while preserving predictive performance. Recent systematic reviews demonstrate that SHAP has been successfully integrated with Random Forest, XGBoost, and LightGBM across numerous financial applications, including credit risk assessment, financial distress prediction, portfolio optimization, and macroeconomic forecasting.

Taken together, the literature reveals three interrelated gaps. First, tourism resilience research remains predominantly centered on tourism-specific performance and recovery indicators, with limited integration of macro-financial resilience. Second, the joint roles of tourism dependency, financial robustness, and persistent global uncertainty remain insufficiently examined within a unified empirical framework. Third, although machine-learning methods are increasingly used in tourism forecasting, their integration with panel econometric inference and explainable AI remains limited in the analysis of tourism financial resilience. Addressing these gaps provides the principal motivation for the conceptual and empirical framework developed in this study.

3. Conceptual Framework

3.1 Theoretical Background

Inspired by Dynamic Capabilities Theory (DCT) while incorporating complementary insights from Complex Adaptive Systems Theory (CAST) and Financial Resilience Theory, this research contributes to understanding how tourism-dependent economies adapt to ongoing global uncertainty. The integration of these theoretical perspectives provides a multidimensional framework capable of explaining why some tourism-dependent economies maintain financial stability during external shocks whereas others experience prolonged economic vulnerability.

Dynamic Capabilities Theory, proposed by Teece and Pisano (1994) and elaborated by Teece (2007, 2018), posits that sustainable competitive advantage arises not from the possession of valuable resources, but via the capacity for the constant integration, construction, and re-arrangement of internal and external capabilities in response to rapidly changing environmental factors. Dynamic Capabilities Theory, in contrast to the Resource-Based View that is primarily concentrated on resource ownership, emphasizes organizational capacity to adapt under volatile environments. Adaptive capability is, therefore, of primary importance as opposed to finite resource endowment capacity, when the environment with technological disruption, financial instability, geopolitical conflicts, or macroeconomic uncertainty is very volatile.

Whereas Dynamic Capabilities Theory originally focused on the characteristics of firm-level strategic adaptation, it has been expanded to tourism destinations and national tourism systems in recent research. Tourism destinations are persistently confronted with external shocks, from pandemics, financial crises, geopolitical conflicts, climate-related disasters, or technological transformation, that demand iterative sensing, learning, resource reconfiguration, and institutional adaptation. Recent research reveals that destinations with stronger adaptive capabilities tend to be much more resilient – in that they are able to redesign tourism products, accelerate digital transformation, coordinate stakeholders, and restore tourism activities faster in the context of large-scale disruption.

However, Dynamic Capabilities Theory alone cannot fully explain resilience at the macroeconomic level because tourism-dependent economies operate as complex adaptive systems composed of interconnected financial markets, governments, firms, households, infrastructure, and international tourism networks. Therefore, this study complements Dynamic Capabilities Theory with Complex Adaptive Systems Theory. The CAST model treats economies as nonlinear systems in which interactions among heterogeneous agents produce emergent outcomes that cannot be accounted for by studying individual components independently. Destinations in tourism constantly evolve through interactions among tourists, governments, financial institutions, transportation networks, digital platforms, and local communities. External shocks are therefore transmitted throughout the tourism system via multiple transmission channels, producing nonlinear responses rather than proportional adjustments.

In the post-pandemic period, tourism systems increasingly show that they may not be linear. Global uncertainty impacts consumer confidence, international mobility, exchange rates, capital flows, investment decisions, inflation expectations, and fiscal sustainability all at once. These interlinked mechanisms amplify financial vulnerability among tourism-dependent economies since tourism revenues constitute a major source of foreign exchange earnings, employment, fiscal revenues, and private investment. Therefore, the resilience of tourism cannot be properly understood by looking only at tourism demand alone, but requires simultaneous consideration of macro-financial stability and systemic adaptive capacity.

The third pillar of the proposed conceptual framework is provided by Financial Resilience Theory. Financial resilience is an economic system's capacity to absorb macro-financial disturbances while maintaining fiscal sustainability, external balance, financial stability, and economic functionality. Financial resilience, unlike traditional macroeconomic stability, has to do with the resilience of the economy during long stretches of uncertainty in an economic system through sufficient liquidity, diversified economic structures, sound financial institutions, prudent fiscal management, and adaptive policy responses. In tourism-reliant economies, it is the financial resilience that ultimately decides whether transient tourism shocks develop into widespread macroeconomic crises or remain manageable sectoral disturbances.

At the macroeconomic level, financial resilience may therefore be understood as an economy's capacity not merely to maintain financial stability in normal periods, but to preserve essential economic functions, mobilize financial buffers, and facilitate adjustment following adverse shocks. In this study, this perspective is operationalized through external-balance capacity and reserve adequacy, which represent financial buffers available to tourism-dependent economies when external revenues decline. Accordingly, financial robustness is treated not as an element of tourism performance itself, but as a distinct shock-absorption capacity that may condition the relationship between tourism dependency, global uncertainty, and tourism financial resilience.

Taken together, these three theoretical perspectives provide a complementary framework for understanding Tourism Financial Resilience. Dynamic Capabilities Theory explains how economies develop and reconfigure adaptive capabilities in response to external shocks; Complex Adaptive Systems Theory captures the nonlinear interactions among tourism, financial, and institutional subsystems; and Financial Resilience Theory explains how macro-financial buffers contribute to an economy's capacity to absorb and adjust to prolonged disturbances. Their integration therefore provides a broader theoretical foundation for Tourism Financial Resilience than any single perspective considered in isolation.

3.2 Research Model and Hypotheses

Building on the theoretical framework above, this study develops a unified conceptual model linking tourism dependency, financial robustness, and global uncertainty to Tourism Financial Resilience. The model conceptualizes resilience as a multidimensional outcome associated with tourism exposure, macro-financial shock-absorption capacity, and the external uncertainty environment, while allowing financial robustness to condition the associations of tourism dependency and global uncertainty with resilience.

The dependent variable is the Tourism Financial Resilience Index (TFRI), constructed through Principal Component Analysis (PCA). The index combines tourism-receipts growth, international tourist-arrivals growth, real GDP growth, inverse unemployment, and inverse inflation, thereby capturing common variation across tourism performance, macroeconomic activity, labour-market conditions, and price stability. Financial robustness is measured separately to avoid conceptual and mechanical overlap with the dependent variable.

The first explanatory variable is Tourism Dependency (TD). Dependence on tourism is a scale indicator of the importance of tourism as a driver of national economic activity, namely, GDP, exports, employment, as well as foreign exchange. The dependency on tourism might further enhance resilience by promoting investment, jobs, building infrastructure, and gaining international advantages. But too much dependence can also heighten vulnerability to external shocks, by confining economic activity to one sector with high levels of cyclicity. Previous empirical evidence has, therefore, demonstrated that tourism dependency both stabilizes and destabilizes depending on related institutional and financial situation. This paper’s claim is that tourism dependency, when supported by strong macro-financial fundamentals, provides strong support to financial resilience.

H1: *Tourism dependency has a positive effect on Tourism Financial Resilience.*

The second principal explanatory factor is financial robustness. Stronger external balances, adequate international reserves, sound financial conditions, and greater macroeconomic policy space can enhance an economy's capacity to absorb sector-specific and external shocks without allowing them to develop into broader macroeconomic instability. In tourism-dependent economies, such financial buffers may be particularly important because sudden declines in tourism receipts can place pressure on foreign-exchange earnings, liquidity conditions, and fiscal resources. Financially robust economies are therefore better positioned to support adjustment through stabilization measures, liquidity provision, and targeted policy responses during periods of external stress. Accordingly, stronger financial robustness is expected to be positively associated with Tourism Financial Resilience.

H2: *Financial robustness positively influences Tourism Financial Resilience.*

The third explanatory construct is Global Uncertainty. In line with Complex Adaptive Systems Theory, uncertainty has a dual effect on tourism demand, financial markets, exchange rates, capital flows, and investment decisions. Increased uncertainty diminishes household confidence, deters foreign travel, raises financing expense, and depresses economic growth. Tourism-dependent economies are particularly susceptible as reductions in tourism revenue will immediately impact fiscal balances, foreign exchange earnings, and employment. Accordingly, continued high global uncertainty will be expected to reduce Tourism Financial Resilience.

From the standpoint of Dynamic Capabilities Theory, economies with higher adaptive capacities are predicted to reconfigure tourism and financial resources more efficiently in the face of external shocks. On the other hand, ongoing global uncertainty lessens the value of these adaptive mechanisms by raising the costs of financing, depleting the demand for tourism and impeding fiscal flexibility. Thus, uncertainty is theoretically expected to reduce Tourism Financial Resilience.

H3: *Global uncertainty negatively affects Tourism Financial Resilience.*

The moderating role of financial robustness can be derived from the joint logic of Dynamic Capabilities Theory and Financial Resilience Theory. External financial buffers may provide tourism-dependent economies with greater capacity to reallocate resources, stabilize external payments, and maintain policy flexibility when tourism revenues or global conditions deteriorate. Financial robustness may therefore condition the relationship between tourism dependency and resilience by reducing the vulnerability associated with sectoral concentration. Similarly, stronger external-balance capacity and reserve adequacy may alter the extent to which persistent global uncertainty is transmitted into tourism-related financial stress. Accordingly, the following moderation hypotheses are proposed.

H4: *Financial robustness positively moderates the relationship between tourism dependency and Tourism Financial Resilience.*

H5: *Financial robustness weakens the negative effect of global uncertainty on Tourism Financial Resilience.*

Figure 1 illustrates the proposed conceptual framework. Tourism dependency, financial robustness, and global uncertainty constitute the principal determinants of Tourism Financial Resilience, while financial robustness simultaneously functions as a strategic buffering mechanism against external shocks. This integrated framework provides the theoretical foundation for the empirical analyses presented in the subsequent sections and directly motivates the development of the Tourism Financial Resilience Index and the hybrid panel econometric–explainable machine learning methodology adopted in this study.

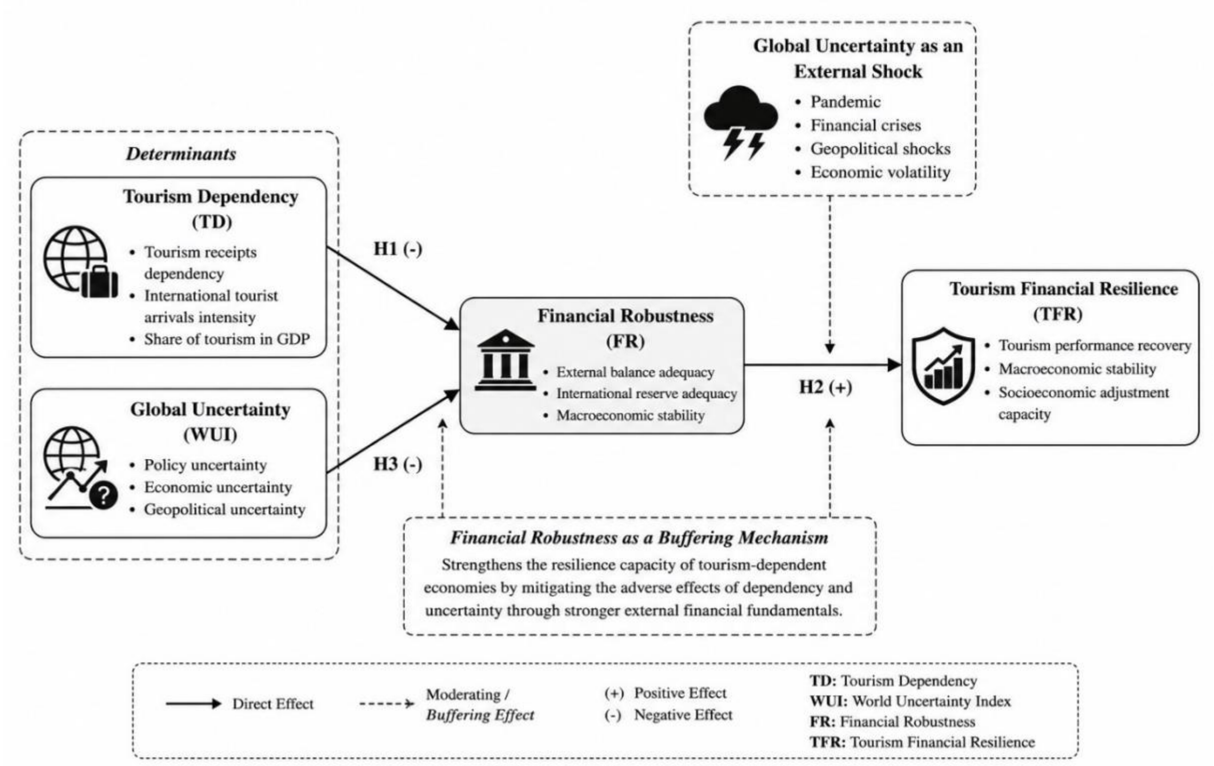

Figure 1. Conceptual Framework of the Determinants of Tourism Financial Resilience

Source: Authors' own conceptualization based on Dynamic Capabilities Theory (Teece, 2007), Complex Adaptive Systems Theory (Holland, 2006), and Financial Resilience Theory.

4. Data and Methodology

4.1 Data

This study uses an unbalanced cross-country panel dataset to assess determinants of financial resilience in tourism-dependent economies under persistent global uncertainty conditions. The empirical analysis focuses on 144 tourism-dependent countries examined from 2010 through 2020, yielding a final estimation sample of 1,533 country-year observations after applying data-quality and minimum-coverage requirements. The observation window was determined by the availability of internationally comparable tourism statistics across all principal data sources. While the initial research design intended to carry on with the analysis until 2025, internationally harmonized tourism indicators show considerable deterioration in cross-country coverage after 2020. Thus restricting the analysis to the 2010–2020 period preserves international comparability, minimizes sample-selection bias, and avoids the use of extrapolated or artificially generated observations.

The empirical dataset combines information from multiple international databases. The tourism indicators were sourced from the World Development Indicators (WDI) released by the World Bank, where tourism statistics are assembled from the official databases of UN Tourism (formerly UNWTO) and supplemented by the International Monetary Fund (IMF) where appropriate (World Bank, 2026). Macroeconomic variables have been collected as WDI, that integrate information coming from IMF Balance of Payments Statistics, the International Financial Statistics, and other internationally standardized statistical systems (World Bank, 2026) including GDP per capita, unemployment, inflation, current-account balance, and international reserves. Global uncertainty was measured through the World Uncertainty Index (WUI) developed by Ahir et al. (2022), which quantifies uncertainty through text-based analysis of Economist Intelligence Unit country reports.

Countries were chosen based on two sets of objective criteria that were applied to guarantee enough exposure to international tourism, while still enabling a certain amount of time horizon for panel estimation. First, tourism receipts had to be at least 3% of total exports, on average, during the period on which we were observing. This measure indicates economies in which tourism is a relevant source of foreign exchange earnings which is economically meaningful and not a marginal type of business activity. Second, the countries were expected to have at least five annual observations of the principal variables included in the analysis.

Based on these screening procedures, 145 countries were selected. It was found that only 144 countries and 1,533 country-year observations were part of this estimation sample, after accounting for observations that were not sufficiently complete.

The principal explanatory variable is Tourism Dependency (TD), measured as international tourism receipts as a percentage of total exports. This indicator has become one of our most widely accepted indicators of tourism dependence because it shows which country's export structure depends most on foreign-exchange earnings generated by tourism. For example, in general higher-value countries will be more exposed to fluctuations of international tourist demand or external shocks, which can damage the movement across borders.

The Financial Robustness Index (FR) was constructed separately from the dependent variable to avoid conceptual overlap and measure countries' capacity to absorb external macro-financial disturbances. The index combines two internationally recognized indicators: current-account balance (% of GDP) and total international reserves (% of GDP). The current-account balance reflects external financing requirements and the sustainability of international transactions, whereas international reserves represent a country's ability to stabilize exchange markets, finance temporary external imbalances, and mitigate sudden disruptions in tourism-generated foreign-exchange inflows.

Global uncertainty is the third major explanatory factor. Using the GDP-weighted World Uncertainty Index, which aggregates uncertainty across national economies while accounting for differences in economic size, the study is based on a series-by-scale comparison method (Ahir et al., 2022). These observations of WUI were recoded from quarterly to annual frequency using calendar-year averages. The resulting variable accounts for common global uncertainty as a result of geopolitical tensions, financial instability, pandemics, and international policy uncertainty, thus mapping the external environment jointly facing all tourism-dependent economies.

Various additional control variables were included to reduce omitted-variable bias and isolate the effects of tourism dependency and financial robustness. GDP per capita (in constant US dollars) controls for differences in economic development and productive capacity, while tourist-arrival intensity measures international tourist arrivals per 1,000 inhabitants relative to the country's population size to account for differences in tourism scale relative to population size. These controls account for structural heterogeneity across countries that may influence resilience independently of a country's dependence on tourism.

Continuous variables were checked for internal consistency and winsorized at the 1st and 99th pooled percentiles to reduce the influence of extreme observations while preserving genuine crisis episodes. Short internal missing-data gaps of up to two consecutive years were addressed using within-country linear interpolation where appropriate, while remaining missing values were treated using iterative multivariate imputation. For variables subject to natural non-negativity constraints, particularly international tourist arrivals and population-based tourism intensity measures, imputation was performed on the underlying source variables rather than directly on the derived ratio. Tourist Arrivals Intensity (ARRINT) was subsequently recalculated as international tourist arrivals per 1,000 population, ensuring consistency with its theoretical measurement scale. Countries with fewer than five annual observations were excluded from the final estimation sample.

Table 1 summarizes the operational definitions, measurement scales, and original data sources of all variables employed in the empirical analysis.

Table 1. Definitions, Measurements, and Data Sources of Variables

Variable	Definition	Measurement	Expected Sign	Source
TFRI	Tourism Financial Resilience Index (Dependent Variable)	First principal component derived from tourism receipts growth, tourist arrivals growth, GDP growth, inverse inflation, and inverse unemployment	Dependent Variable	Authors' calculations using PCA
TD	Tourism Dependency	International tourism receipts (% of total exports)	+	World Bank (2026); UN Tourism
FR	Financial Robustness Index	First principal component derived from Current Account Balance (% GDP) and International Reserves (% GDP)	+	World Bank (2026); IMF
WUI	Global Uncertainty	GDP-weighted World Uncertainty Index	–	Ahir et al. (2022)
GDPPC	Economic Development	Natural logarithm of GDP per capita (constant US$)	+	World Bank (2026)
ARRINT	Tourism Intensity	International tourist arrivals per 1,000 population	+	World Bank (2026); UN Tourism

Source: Authors' compilation based on the World Bank (2026), International Monetary Fund (2026), UN Tourism (2026), and Ahir et al. (2022).

Table 1 shows that the empirical framework combines tourism-specific indicators, macro-financial variables, and global uncertainty measures to examine tourism financial resilience in a multidimensional way. While previous studies only included specific indicators of tourism performance or destination recovery, the proposed framework incorporates tourism dependence, external financial strength, macroeconomic stability, and global uncertainty. As a result, the empirical specification allows for a more comprehensive assessment of critical elements that drive resilience in tourism-dependent economies amid adverse global conditions.

4.2 Methodology

The investigation of underlying factors of tourism financial resilience under global uncertainty through a hybrid empirical framework based on multivariate statistical analysis, panel econometrics, panel quantile regression, machine learning, and explainable artificial intelligence (XAI) has been performed in this study. In contrast with traditional tourism research that relies exclusively on linear panel regressions, the presented framework simultaneously estimates average effects, heterogeneous effects across different levels of resilience, nonlinear relationships, and variable importance. Thus, the framework combines robust statistical inference with a complementary assessment of nonlinear predictive patterns and model-based variable importance.

4.2.1 Construction of the Tourism Financial Resilience Index

The main purpose of this research is to propose a multi-dimensional assessment capable of assessing the financial resilience of tourism-dependent economies in a world of prolonged international instability. Contrary to traditional tourism performance indicators, which are mainly concerned with tourism demand assessment, competitiveness of destinations, and visitor recovery, the adopted Tourism Financial Resilience Index (TFRI) simultaneously incorporates tourism dynamics and macroeconomic stability. This theory aligns with the conceptual framework introduced in the previous section by which it is argued that resilience should not be interpreted solely as the recovery of tourism activity but rather as the ability of an economy to maintain macro-financial stability while preserving tourism performance during periods of severe external disruption.

Composite indicators are being increasingly designed in tourism economics, resilience analysis, and sustainable development because resilience is a multidimensional phenomenon that cannot be adequately represented by any one observable variable (OECD, 2008; Jolliffe & Cadima, 2016). Indicators of resilience can only reflect one aspect of a complex phenomenon, which means that interpretation of these indicators in isolation often results in either incomplete or misleading evidence. Composite indices compensate for this constraint by pooling related indicators into a common latent construct that captures the common variation within multiple dimensions of the underlying phenomenon.

This study thus develops a Tourism Financial Resilience Index employing Principal Component Analysis (PCA). PCA is a multivariate statistical approach which transforms a set of correlated variables into a small number of mutually orthogonal components while retaining the maximum proportion of the variance contained in the original dataset (Jolliffe & Cadima, 2016). Relative to arbitrary weighting schemes or equal-weight composite indices, PCA extracts the weights from the covariance structure of observed variables, yielding data-determined weightings. Thus, the index obtained reduces subjectivity of indicator aggregation and is statistically robust for encapsulating the latent resilience construct.

Prior to estimating the principal components, all variables were standardized to eliminate differences in measurement scales. Standardization ensures that variables measured in different units contribute proportionally to the covariance matrix and prevents variables with larger numerical ranges from dominating the principal components. Each variable was transformed into a standardized score according to the following expression:

$$Z_{\{ij\}} = \{X_{\{ij\}} - \{\bar{X}\}_{\{j\}}\}/\{s_{\{j\}}\}$$

where $Z_{\{ij\}}$ denotes the standardized value of variable *(j)* for country *(i)*, $X_{\{ij\}}$ represents the original observation, $\{\bar{X}\}_{\{j\}}$ *is the sample mean, and* $s_{\{j\}}$ denotes the corresponding standard deviation. Standardization produces variables with a mean of zero and a standard deviation of one, thereby ensuring comparability across indicators before dimension reduction.

The Tourism Financial Resilience Index was subsequently obtained from the first principal component extracted from the standardized data matrix. Mathematically, the composite index is expressed as

$$TFRI_i = \sum_{\{j=1\}}^{\{k\}} \left(\lambda_j Z_{\{ij\}}\right)$$

where $TFRI_i$ denotes the Tourism Financial Resilience Index for country *(i)*, $Z_{\{ij\}}$ represents the standardized value of indicator *(j)*, *(k)* is the number of indicators included in the index, and λ_j denotes the loading associated with indicator *(j)* in the first principal component.

The first principal component was retained because it explains the largest proportion of the total standardized variance among the underlying indicators and therefore provides the most parsimonious representation of the common resilience dimension. Consistent with the recommendations of Jolliffe and Cadima (2016), no rotation procedure was applied because the objective was dimension reduction rather than latent-factor interpretation.

Although the first principal component explains 43.29% of the total standardized variance, its eigenvalue exceeds unity (2.164), and all five indicators load in the theoretically expected direction. The component is dominated by tourism-arrivals growth, real GDP growth, and tourism-receipts growth, whereas inverse unemployment and inverse inflation provide smaller complementary contributions. Accordingly, the TFRI should be interpreted primarily as a parsimonious common resilience dimension rather than as an exhaustive representation of every dimension of tourism-related financial resilience.

The five indicators were selected on theoretical and empirical grounds before creating the Tourism Financial Resilience Index. Growth in tourism receipts and growth in international tourist arrivals represent the capacity of the tourism industry to recover following external disturbances. Real GDP growth reflects the broader macroeconomic ability to sustain productive activity during adverse periods. Inflation and unemployment entered the index with reversed orientation because lower inflationary pressures and stronger labour-market conditions are generally associated with greater macroeconomic resilience and higher adaptive capacity. In combination, these variables reflect complementary dimensions of tourism performance, economic stability, and socioeconomic adjustment that collectively describe tourism financial resilience.

Empirical PCA findings obtained based on 144 countries in the sample and 1,533 country-year observations show that the first principal component accounts for 43.29% of the total standardized variance in the five indicators. In terms of loading matrix, the biggest positive contributions come from the growth in international tourist arrivals (0.577), real GDP growth (0.563), and the growth in tourism receipts (0.560), followed by inverse unemployment (0.177) and inverse inflation (0.069). These loading patterns indicate that tourism recovery and overall macroeconomic performance occupy dominant positions as drivers of tourism financial resilience in the sample economies, with labour-market stability and price stability supporting complementary but less important roles.

The positive loading pattern in all the variables suggests that higher tourism growth, stronger economic expansion, lower unemployment, and lower inflation positively affect the magnitude of the value of the Tourism Financial Resilience Index. As a result, higher TFRI scores indicate a stronger adaptive capacity, higher macroeconomic stability, and a higher ability to withstand external tourism-related shocks. In contrast, poorer index values signpost countries with recurring tourism contractions, weaker macroeconomic performance, and less resilience in times of high global uncertainty.

Macro-financial capacity was quantified with a separate Financial Robustness Index (FR) to prevent conceptual overlap of the dependent variable and the explanatory variables. Setting up an independent measure for financial capacity makes it less likely that the dependent variable and its external factors may mechanically affect each other to create a correlation, and it enables financial resilience to be investigated as an explanation, not a part of the dependent variable.

By the same statistical procedure used in the TFRI, the Financial Robustness Index was constructed using Principal Component Analysis based on two internationally comparable macro-financial indicators: current account balance (% of GDP) and international reserves (% of GDP). And finally, both variables are widely considered in international macroeconomic literature as important indices of external sustainability and financial shock-absorption capacity, because they share a characteristic of the existence or non-existence of an economy to finance foreign imbalances, maintain exchange market stability, and endure rapid declines in foreign-currency earnings.

Unlike traditional composite indicators using subjective weighting algorithms, PCA measures weights objectively based on their respective covariance structures. As a result, indicators exhibiting greater common variation receive larger contributions to the composite index, whereas variables explaining relatively smaller proportions of the common variance receive correspondingly lower weights. This weighting mechanism is supported by data to minimize researcher bias and increase the statistical robustness of the outcome index (Jolliffe & Cadima, 2016).

The composite indices were constructed using the first principal component extracted from standardized underlying indicators. Standardizing the underlying indicators prior to PCA ensures comparability across variables measured on different scales while preserving the variance structure captured by the first principal component. Higher index values indicate stronger tourism financial resilience or financial robustness, whereas lower values indicate comparatively weaker performance.

4.2.2 Econometric and Machine Learning Framework

This study combines panel-data econometrics with machine-learning methods to examine Tourism Financial Resilience from complementary inferential and predictive perspectives. The econometric analysis estimates the direction, magnitude, and statistical significance of conditional associations among tourism dependency, financial robustness, global uncertainty, and Tourism Financial Resilience. The machine-learning component evaluates out-of-sample predictive performance and model-based predictor importance. Integrating these approaches permits robust statistical inference on associations alongside an assessment of nonlinear predictive structure without treating either component as establishing causality (Breiman, 2001; Hastie et al., 2021). The combination of econometric modelling and explainable machine learning is aimed at complementing each other rather than competing. Panel econometric models provide statistically explainable mean and heterogeneous effects given explicit behavioural assumptions, while machine-learning algorithms account for nonlinear relationships, threshold effects, and complex interactions that traditional regression models may fail to capture. The SHAP analysis improves interpretability by pinpointing how individual predictors play a role in predicting models which thus closes the prediction-and policy-relevant explanation-discrepancy.

Given the longitudinal structure of the dataset, consisting of 144 countries observed over the 2010–2020 period (1,533 country-year observations), panel-data econometrics provides the most appropriate analytical framework. Panel datasets simultaneously exploit cross-sectional and time-series variation, allowing researchers to control for unobserved country-specific heterogeneity while substantially improving estimation efficiency relative to purely cross-sectional analyses (Baltagi, 2021). Because countries differ considerably in institutional quality, tourism specialization, macroeconomic structure, and financial development, failure to control for these time-invariant characteristics may produce biased and inconsistent coefficient estimates.

As such, the empirical analysis starts with a country fixed-effects specification. The fixed-effects approach controls for all unobservable characteristics that remain constant within countries over time by permitting each country to have its own intercept. The estimated coefficients therefore only describe within-country variation over the course of the sample, significantly minimizing omitted-variable bias attributable to unobserved heterogeneity (Wooldridge, 2020). Thus, compared to pooled ordinary least squares, the fixed-effects estimator yields much more reliable estimates in the analysis of heterogeneous cross-country panels.

The baseline empirical specification is expressed as follows:

$$TFRI_{it} = \alpha_i + \beta_1 TD_{it} + \beta_2 FR_{it} + \beta_3 WUI_t + \beta_4 (TD \times FR)_{it} + \beta_5\ (WUI \times FR)_{it} + \gamma_1 GDPPC_{it} + \gamma_2\ ARRINT_{it} + \varepsilon_{it}$$

where $TFRI_{it}$ denotes the Tourism Financial Resilience Index for country i in year t. The principal explanatory variable, TD_{it}, measures tourism dependency, while FR_{it} represents the Financial Robustness Index constructed through Principal Component Analysis. Global uncertainty is proxied by the World Uncertainty Index WUI_t, which captures worldwide policy and economic uncertainty affecting all countries simultaneously (Ahir et al., 2022). The interaction terms $(TD \times FR)_{it}$ and $(WUI \times FR)_{it}$ are introduced to investigate whether stronger financial fundamentals moderate the effects of tourism dependence and global uncertainty on tourism financial resilience. Finally, GDP per capita $GDPPC_{it}$ and international tourist arrivals intensity $ARRINT_{it}$ are included as control variables to account for differences in economic development and tourism market size.

Interaction terms are theoretically inspired by the resilience literature that suggests that the impact of external shocks depends not only on the magnitude of the shock itself but also on the adaptive capacity of the affected economy (Briguglio et al., 2009). Economies possessing stronger external financial positions may therefore be better able to absorb adverse tourism shocks arising from elevated global uncertainty. The estimated interaction effects enable the model to extend from average marginal relationships to consider whether financial robustness would enhance or undermine the association of tourism dependence with resilience across varying macroeconomic settings.

The explanatory variables were screened for possible multicollinearity before estimates of the regression models were determined. Despite the significant effect that composite indices generated through Principal Component Analysis have on diminishing linear dependence between the underlying indicators, correlation diagnostics and Variance Inflation Factor (VIF) statistics were also checked to guarantee that no explanatory variable suffers adverse levels of multicollinearity. Diagnostic findings demonstrated that the explanatory variables remain sufficiently independent to permit reliable coefficient estimation, revealing that the estimated regression coefficients are unlikely to be distorted by excessive linear dependence among regressors.

Cross-country macroeconomic panels often demonstrate cross-sectional dependence as countries are all directly affected by common global shocks, from financial crises and pandemics, to geopolitical instability, and worldwide tourism disruptions. Similarly, serial correlation and heteroskedasticity are frequent for macro-panel-based data through their recurring patterns in economic processes and the structural differences between the countries (Hoechle, 2007). Excluding these features of econometrics will create downward-biased standard errors leading to misleading statistical inference, even if the estimates are not influenced by the econometric properties.

For this issue, Driscoll–Kraay heteroskedasticity- and autocorrelation-consistent standard errors are used in our study. The Driscoll–Kraay covariance estimator is tailor-made for macro-panel data with heteroskedasticity, serial correlation, and cross-sectional dependence simultaneously (Driscoll & Kraay, 1998). In contrast to traditional robust covariance estimators, the Driscoll–Kraay approach is asymptotically consistent even when cross-sectional units are correlated through common global shocks. We use the Driscoll–Kraay estimator as the most suitable covariance correction for obtaining statistically reliable inferences given the sample we analyze is comprised of interconnected national economies subjected to the same international uncertainty shocks.

The covariance matrix has been estimated as suggested by Hoechle (2007) with the Bartlett kernel and with an automatically selected bandwidth. This approach to estimation increases the robustness of statistical inference while maintaining the consistency of fixed-effects coefficient estimates. Accordingly, all statistical significance reported throughout the empirical analysis is based on Driscoll–Kraay corrected standard errors, while at the same time guaranteeing that hypothesis testing is indeed valid in the presence of multiple forms of error dependence frequently observed in international macroeconomic panels.

Even so, though, the fixed-effects model with Driscoll–Kraay standard errors provides consistent estimates of the average relationship between the explanatory variables and financial resilience of tourism, it is also based on the assumption that the effects of the regressors remain constant across the conditional distribution of the dependent variable. This assumption might be too simplistic in the case of tourism-dependent economies in that countries show a great diversity in resilience characteristics. Low-resilient economies could react differently to tourism dependency or financial resilience changes than those with stronger adaptive capacities. Therefore, the use of only mean-based estimators can obscure important distributional differences and result in incomplete policy conclusions.

To take this heterogeneity into consideration, we generalize the analysis by employing Panel Quantile Regression (PQR). Created from Koenker and Bassett's (1978) original model and later extended for panel data, quantile regression assesses the conditional effects of explanatory variables at various points in the distribution of the dependent variable (as opposed to just its conditional mean). This approach allows examination of heterogeneous responses for countries that demonstrate varying degrees of resilience, and consequently, offers a significantly better and more complete picture of the underlying economic interrelations (Koenker, 2004).

The conditional quantile model is specified as

$$Q_{(\tau)}\,(TFRI_{it}|X_{it}) = \alpha_i^{(\tau)} + \beta^{(\tau)}X_{it} + \varepsilon_{it}$$

where $Q_{(\tau)}\,(TFRI_{it}|X_{it})$ denotes the conditional τ-th quantile of the Tourism Financial Resilience Index; $\alpha_i^{(\tau)}$ represents the country-specific fixed effect; X_{it} is the vector of explanatory variables; $\beta^{(\tau)}$ is the vector of quantile-specific coefficients; and ε_{it} denotes the error term. Unlike conventional panel estimators, the coefficients obtained from Panel Quantile Regression are allowed to vary across different segments of the conditional distribution, thereby revealing whether the determinants of tourism financial resilience differ between relatively vulnerable and relatively resilient economies.

Following the standard practice in empirical macroeconomic and tourism research, the model is estimated for the 25th, 50th, and 75th conditional quantiles ($\tau = 0.25, 0.50$, and 0.75). The lower quantile represents countries with relatively weak tourism financial resilience, the median quantile reflects economies with average resilience characteristics, whereas the upper quantile corresponds to countries exhibiting comparatively stronger adaptive capacity. Estimating these three quantiles enables the analysis to investigate whether the effects of tourism dependency, financial robustness, and global uncertainty remain stable across different resilience regimes or vary systematically with the resilience level of individual economies.

In general, the inclusion of Panel Quantile Regression comes at a special interest for global tourism since international crises rarely impact all destinations equally. Events such as the COVID-19 pandemic, global financial crises, geopolitical conflicts, or widespread policy uncertainty affect the distribution disproportionately in countries' institutional quality, financial preparedness and tourism specialization. Therefore, the marginal contribution made by financial robustness may be higher amongst tourism-dependent economies that are highly susceptible to shocks than those with good macroeconomic fundamentals. Quantile regression represents a strong tool to identify these heterogeneous responses that cannot be observed with conventional mean-regression methods.

Methodologically, Panel Quantile Regression also affords critical robustness benefits. Firstly, the estimator is considerably less sensitive to extreme observations and non-normal error distributions than ordinary least squares estimators, because it minimizes weighted absolute deviations rather than squared residuals (Koenker & Bassett, 1978). This is especially useful when dealing with international macroeconomic data, since large cross-country differences and exceptional crisis episodes often produce outliers. Secondly, quantile regression does not require homoscedastic error terms and is especially suitable for heterogeneous panels with substantial cross-country variation in economic size, tourism intensity, and institutional development. Third, by estimating multiple conditional quantiles simultaneously, the method enables a comprehensive assessment of parameter stability across the entire distribution of tourism financial resilience.

This makes the combination of fixed-effects estimation and Driscoll–Kraay covariance correction as well as Panel Quantile Regression a complementary econometric framework and not alternatives for estimation. The fixed-effects model identifies the average within-country relationship while accounting for unobserved heterogeneity and cross-sectional dependence. Panel Quantile Regression then tests if these average effects are consistent across economies with different resilience capacities. The two approaches show agreement, which increases the robustness of the empirical results, while the systematic difference between the quantiles suggests heterogeneous adjustment mechanisms that would not be identified by a standard mean-regression analysis.

In this manner, the present paper's econometric approach is intended to achieve a trade between statistical rigor and meaningful interpretation. The fixed-effects model with Driscoll–Kraay standard errors provides robust inference on within-country associations under heterogeneous macro-panel conditions, while Panel Quantile Regression evaluates whether these associations vary across different points of the conditional distribution of Tourism Financial Resilience. Together, these approaches provide complementary evidence on average and distributional associations before proceeding to the machine-learning analysis, which focuses on out-of-sample prediction and model-based variable importance.

Panel econometric models provide statistically rigorous evidence regarding the direction and significance of the relationships among the study variables, but are primarily designed for inference rather than prediction. The emergence of expansive international data sets in recent years led researchers to complement traditional econometric procedures with machine-learning algorithms capable of modelling complex, nonlinear, and high-order interactions among variables (Hastie et al., 2021). Accordingly, this study integrates explainable machine-learning techniques into the empirical framework to evaluate predictive performance and to identify the relative importance of the determinants of tourism financial resilience.

Three supervised ensemble-learning algorithms including Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM) were used. These algorithms were chosen based on their better predictive ability in empirical work and practical applications covering macroeconomic prediction, financial risk analysis and tourism demand prediction (Breiman, 2001; Chen & Guestrin, 2016; Ke et al., 2017). Ensemble-based learning models do not assume linearity, homoscedasticity, or normally distributed residuals, as is the case for conventional linear regression models. Rather they identify nonlinearity, interaction effects, and complex decision boundaries that frequently characterize international macroeconomic data. Model hyperparameters were optimized with grid searching and five-fold cross-validation to reduce the prediction error and overfitting.

The Random Forest is one of the most robust non-parametric learning algorithms among ensemble-based learning techniques. Introduced by Breiman (2001), Random Forest generates a large number of decision trees based on bootstrap samples from the original dataset after randomly selecting subsets of explanatory variables at each splitting node. Final predictions are computed by averaging the predictions from individual trees, thus significantly reducing forecast variance and minimizing the risk of overfitting. Random Forest acts very well where predictor variables have moderate correlation and nonlinear interaction due to its bootstrap aggregation (bagging) model.

While Random Forest generates stable predictions, boosting algorithms often achieve better predictive performance by taking a sequential approach for correcting the prediction errors of previous trees. This led to the current work utilizing Extreme Gradient Boosting (XGBoost), which has emerged as one of the most widely used machine-learning algorithms in economics and finance. XGBoost iteratively builds trees by minimizing a regularized objective function using second-order gradient optimization to enable improved computational efficiency and predictive performance (Chen & Guestrin, 2016). Incorporating regularization terms controlling the complexity of trees also reduces overfitting, thus making the resulting algorithm more generalizable through analysing heterogeneous macroeconomic datasets.

The empirical analysis also integrates Light Gradient Boosting Machine (LightGBM) to provide an additional benchmark. Developed by Ke et al. (2017), LightGBM differs from regular boosting algorithms by using a histogram approach to study learning and the leaf-wise growth in trees instead of the conventional level-wise expansion. This architecture significantly accelerates model estimation and increases predictive accuracy for large-scale datasets with many observations and explanatory variables. LightGBM, therefore, should provide an adequate algorithm for analysing international panel datasets that represent heterogeneous economic structures and potentially complex nonlinear relationships between tourism, macroeconomic, and financial variables.

In order to obtain a realistic assessment of forecast performance, model estimation was based on a temporal hold-out validation method, as opposed to random sampling. 2010–2017 observations were employed to develop the algorithms, and 2018–2020 observations were reserved exclusively for out-of-sample testing. This method avoids information leakage between test and training samples and is closely aligned with realistic forecasting contexts where future observations are not present during the model estimation phase (Hastie et al., 2021). In addition, chronological data partitioning is of particular significance for macroeconomic purposes where observations are ordered over time.

The explanatory variables provided to each algorithm are the same regressors as the ones presented in the econometric models: tourism dependency, the Financial Robustness Index, the World Uncertainty Index, GDP per capita, tourist-arrival intensity, and the interaction terms between financial robustness and the principal explanatory variables. Using an identical set of predictors ensures direct comparability between econometric inference and machine-learning prediction while preventing differences in variable selection from influencing the comparative evaluation of model performance.

Predictive accuracy was assessed using three widely accepted performance measures: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). These indicators jointly evaluate the magnitude of prediction errors and the proportion of variation explained by each algorithm.

The Mean Absolute Error is calculated as

$$MAE = \left(\frac{1}{n}\right)\Sigma|y_i - \hat{y}_i|$$

where y_i denotes the observed value of the Tourism Financial Resilience Index and $\hat{y}_i$ represents the corresponding predicted value. Lower MAE values indicate greater predictive accuracy because they imply smaller average prediction errors.

The Root Mean Squared Error is defined as

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right)\times \Sigma(y_i - \hat{y}_i)^2\right]}$$

which assigns greater weight to larger prediction errors due to the squaring operation. Consequently, RMSE is particularly informative when evaluating forecasting models intended to capture extreme observations associated with periods of elevated global uncertainty.

Finally, explanatory power was evaluated using the coefficient of determination,

$$R^2 = 1 - \left[\frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y})^2}\right]$$

where ȳ denotes the sample mean of the dependent variable. Higher R^2 values indicate superior predictive performance through a larger proportion of explained variation.

Although ensemble-learning algorithms frequently achieve high predictive accuracy, they are commonly criticized for operating as black-box models, making it difficult to interpret how individual predictors influence model outputs. To overcome this limitation, the present study employs SHapley Additive exPlanations (SHAP) as a post-estimation interpretability framework (Lundberg & Lee, 2017). SHAP combines concepts from cooperative game theory with additive feature attribution to quantify the marginal contribution of each explanatory variable to individual predictions.

Formally, the prediction generated by the machine-learning model can be decomposed as

$$f(x) = \varphi_0 + \sum\varphi_j$$

where $f(x)$ denotes the predicted value of the Tourism Financial Resilience Index, φ_0 represents the baseline prediction, and φ_j measures the Shapley value associated with explanatory variable j. Larger mean absolute SHAP values indicate a greater overall contribution of each predictor to the model's predictions, irrespective of effect direction.

In contrast to traditional feature-importance measures, SHAP provides global and local interpretability. Global explanations give overall importance information for each predictor of an entire dataset, while local explanations, on the other hand, indicate the degree to which given variables influence the prediction for individual country-year observations. This two-fold view greatly clarifies machine-learning outputs and permits us to directly compare them with the coefficient estimates provided by the panel econometric models. Thus, SHAP complements the panel econometric analysis by providing transparent interpretation of nonlinear relationships that cannot be inferred from regression coefficients directly.

Importantly, SHAP values quantify each predictor's contribution to the fitted model predictions and should not be interpreted as estimates of causal effects. Accordingly, the SHAP analysis is used here to assess model-based predictor importance and nonlinear predictive associations rather than causal influence.

5. Results

5.1 Econometric Results

The empirical analysis begins with an examination of the descriptive characteristics of the dataset, followed by correlation analysis and the evaluation of the principal component structures used to construct the composite indices. These preliminary analyses provide important evidence regarding the statistical properties of the variables and verify the suitability of the proposed composite measures before proceeding to the econometric estimations.

Table 2. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Tourism Financial Resilience Index (TFRI)	1,533	0.000	1.472	−6.476	4.281
Tourism Dependency (TD)	1,533	20.700	21.874	0.641	88.206
Financial Robustness Index (FR)	1,533	0.000	1.074	−2.775	5.262
World Uncertainty Index (WUI)	1,533	24,923.39	6,939.629	16,795.843	40,648.575
GDP per capita (log) (GDPPC)	1,533	8.730	1.404	6.037	11.692
Tourist Arrivals Intensity (ARRINT)	1,533	2,204.402	6,876.118	−9,577.516	58,351.163

Notes: FRI and FR are composite indices constructed using Principal Component Analysis (PCA) from standardized underlying indicators. GDPPC denotes the natural logarithm of GDP per capita (constant US$). ARRINT represents international tourist arrivals per 1,000 population. The final unbalanced panel comprises 144 tourism-dependent countries and 1,533 country-year observations over the 2010–2020 period.

Table 2 presents the descriptive statistics for the variables included in the empirical analysis. The final unbalanced panel comprises 1,533 country-year observations across 144 tourism-dependent countries over the 2010–2020 period. The Tourism Financial Resilience Index (TFRI) has a mean of approximately zero and a standard deviation of 1.472, with values ranging from −6.476 to 4.281, indicating substantial variation in tourism financial resilience across the sample. Tourism Dependency (TD) also exhibits considerable dispersion, with a mean of 20.700 and values ranging from 0.641 to 88.206. The Financial Robustness Index (FR) is centered around zero, while the World Uncertainty Index (WUI) displays substantial variation over the sample period. Overall, the descriptive statistics indicate considerable heterogeneity across the countries included in the analysis.

To examine the linear associations among the study variables, Table 3 presents the Pearson correlation matrix. The Tourism Financial Resilience Index is moderately and negatively correlated with the World Uncertainty Index ($r = -0.348$), providing preliminary evidence of an inverse association between global uncertainty and tourism financial resilience. Among the explanatory variables, the largest pairwise correlation is observed between Tourism Dependency and Tourist Arrivals Intensity ($r = 0.442$), followed by GDP per capita and Tourist Arrivals Intensity ($r = 0.371$) and Financial Robustness and GDP per capita ($r = 0.331$). None of the pairwise correlations among the explanatory variables is sufficiently high to indicate severe multicollinearity. Formal multicollinearity diagnostics are additionally assessed using Variance Inflation Factor (VIF) statistics.

Table 3. Pearson Correlation Matrix

Variable	TFRI	TD	FR	WUI	GDPPC	ARRINT
TFRI	1.000					
TD	0.011	1.000				
FR	−0.012	−0.088	1.000			
WUI	−0.348	0.006	0.037	1.000		
GDPPC	−0.183	0.051	0.331	0.024	1.000	
ARRINT	−0.017	0.442	0.185	0.004	0.371	1.000

Notes: The table reports pairwise Pearson correlation coefficients. TFRI denotes the Tourism Financial Resilience Index; TD, Tourism Dependency; FR, Financial Robustness Index; WUI, World Uncertainty Index; GDPPC, the natural logarithm of GDP per capita; and ARRINT, Tourist Arrivals Intensity.

Although the correlation analysis provides preliminary evidence regarding the linear relationships among the variables, the validity of the proposed composite indices should also be evaluated empirically. Accordingly, Principal Component Analysis (PCA) was performed to construct both the Tourism Financial Resilience Index (TFRI) and the Financial Robustness Index (FR). Table 4 presents the factor loadings and principal component statistics obtained from the PCA estimations.

Table 4. Principal Component Analysis (PCA) Results

Panel A. Tourism Financial Resilience Index (TFRI)

Indicator	Component Loading	Communality
Tourism receipts growth	0.560	0.314
Tourist arrivals growth	0.577	0.333
Real GDP growth	0.563	0.317
Inverse unemployment	0.177	0.031
Inverse inflation	0.069	0.005
PCA Statistics	**Value**	
First Principal Component	PC1	
Eigenvalue	2.164	
Explained Variance (%)	43.29	
Cumulative Variance (%)	43.29	
Number of Indicators	5	

Panel B. Financial Robustness Index (FR)

Indicator	**Component Loading**	**Communality**
Current account balance (% GDP)	0.707	0.500
International reserves (% GDP)	0.707	0.500

PCA Statistics	**Value**
First Principal Component	PC1
Eigenvalue	1.152
Explained Variance (%)	57.59
Cumulative Variance (%)	57.59
Number of Indicators	2

The first principal component explains 43.29% of the total variance. Tourism arrivals growth (0.577), GDP growth (0.563), and tourism receipts growth (0.560) exhibit the highest loadings, indicating that these indicators contribute most strongly to the Tourism Financial Resilience Index.

Table 5. Fixed-Effects Panel Regression Results (Driscoll–Kraay Robust Standard Errors)

Variable	**β**	**p**
TD	1.406	0.101
FR	0.104	0.399
WUI	−0.504	0.022
TD×FR	0.109	0.229
WUI×FR	−0.053	0.006
GDPpc	−0.315	0.663
ARRINT	1.040	<0.001

Table 5 reports the results of the country fixed-effects panel regression models estimated using Driscoll–Kraay robust standard errors. The within R^2 value of 0.275 indicates that the proposed model explains approximately 27.5% of the within-country variation in Tourism Financial Resilience.

Among the explanatory variables, the World Uncertainty Index (WUI) emerges as the most influential macroeconomic determinant of Tourism Financial Resilience. The estimated coefficient is negative and statistically significant ($\beta = -0.504$, $p = 0.022$), indicating that increases in global uncertainty systematically reduce the financial resilience of tourism-dependent economies. This finding supports Hypothesis 3 and is consistent with the theoretical expectation that heightened uncertainty discourages international travel, delays investment decisions, weakens tourism demand, and reduces economies' capacity to absorb external shocks (Ahir et al., 2022; Bloom, 2014).

By contrast, the direct effects of Tourism Dependency (TD) ($\beta = 1.406$, $p = 0.101$) and the Financial Robustness Index (FR) ($\beta = 0.104$, $p = 0.399$) are not statistically significant after controlling for country fixed effects, global uncertainty, and the remaining explanatory variables. These findings indicate that neither tourism specialization nor external financial strength alone is sufficient to explain cross-country differences in Tourism Financial Resilience. Accordingly, Hypotheses 1 and 2 are not supported by the baseline fixed-effects specification.

The interaction terms provide additional insights into the underlying adjustment mechanisms. The interaction between Tourism Dependency and Financial Robustness (TD × FR) is statistically insignificant ($\beta = 0.109$, $p = 0.229$), suggesting that stronger external financial positions do not systematically alter the relationship between tourism dependency and Tourism Financial Resilience. Consequently, Hypothesis 4 is not supported by the fixed-effects model. In contrast, the interaction between Global Uncertainty and Financial Robustness (WUI × FR) is negative and statistically significant ($\beta = -0.053$, $p = 0.006$). This finding indicates that the relationship between global uncertainty and Tourism Financial Resilience varies with countries' macro-financial conditions. However, because the interaction coefficient is negative, the result does not support the hypothesized buffering effect of financial robustness. Accordingly, Hypothesis 5 is not supported in the predicted direction.

Regarding the control variables, Tourist Arrivals Intensity (ARRINT) is the only variable exhibiting a positive and highly significant coefficient ($\beta = 1.040$, $p < 0.001$), indicating that countries attracting larger numbers of international visitors relative to their population tend to exhibit greater Tourism Financial Resilience. In contrast, GDP per capita does not have a statistically significant effect ($\beta = -0.315$, $p = 0.663$), suggesting that higher income levels alone do not necessarily translate into greater resilience once tourism dynamics, financial conditions, and global uncertainty are simultaneously taken into account.

Table 6. Panel Quantile Regression Results

Variable	Q25	Q50	Q75
TD	0.904***	0.906***	0.906***
FR	0.148**	0.150**	0.149**
WUI	-0.313***	-0.316***	-0.316***
TD×FR	0.067	0.066	0.067
WUI×FR	-0.023	-0.021	-0.021
GDPpc	-0.321	-0.322	-0.322
ARRINT	0.899***	0.890***	0.891***

We observe from the estimation results that Tourism Dependency (TD) becomes positive and highly statistically significant across all conditional quantiles, despite being statistically insignificant in the fixed-effects model. This observation indicates that simply using mean-based estimation does not capture the impact of specialization in tourism. Instead, tourism dependency positively underpins tourism financial resilience across the conditional distribution after bearing the differences of resilience regimes explicitly in mind. Thus, the quantile results complement in support of Hypothesis 1 and suggest that the resilience-enhancing role attributed to tourism specialization is more stable than predicted from the average regression.

In a similar vein, the Financial Robustness Index (FR) shows a positive and statistically significant coefficient at the lower, median, and upper quantiles. The quantile results, in contrast to the fixed-effects finding in which the direct effect of financial robustness was not statistically significant, indicate that stronger external financial conditions systematically improve tourism financial resilience across countries with different levels of resilience. It suggests that financial robustness promotes resilience as a broad and persistent mechanism, not only at the conditional mean, further reinforcing evidence for Hypothesis 2.

Consistent with the baseline regression results, the coefficient for the World Uncertainty Index (WUI) is negative and highly significant across all estimated quantiles. The remarkable stability of the estimated coefficients indicates that global uncertainty has a pervasive adverse effect, regardless of whether countries initially exhibit relatively low or relatively high tourism financial resilience. This consistency supports the conclusion that global uncertainty constitutes one of the principal external constraints affecting tourism-dependent economies and provides strong additional support for Hypothesis 3.

Neither interaction term appears to meet traditional statistical significance thresholds in the quantile framework. The non-significant coefficients found on TD × FR and WUI × FR suggest that the moderating effects seen for the fixed-effects model may not be equally spread across the conditional distribution of tourism financial resilience. Rather, it seems that these interaction effects converge around the conditional mean and are not consistently present in cases when countries have particularly low or high resilience rates. Accordingly, the Panel Quantile Regression results provide no statistically significant support for Hypotheses 4 and 5 across the examined quantiles. The significant WUI × FR interaction observed in the fixed-effects model therefore appears to be specification-dependent.

In terms of controls, Tourist Arrivals Intensity (ARRINT) remains positive and statistically significant across the estimated quantiles, indicating a robust positive association between tourist-arrival intensity and Tourism Financial Resilience across different points of the conditional distribution. GDP per capita, on the other hand, still has not reached statistical significance in the dependent variable, indicating that higher economic development not in and of itself is not a guarantor of higher resilience when factors such as tourism, financial situation, as well as global uncertainty are taken into account together.

5.2 Machine Learning Results and Model Interpretation

To complement the panel econometric analysis, this study employs Random Forest (RF), XGBoost, and LightGBM to evaluate predictive performance and capture nonlinear relationships in Tourism Financial Resilience. Predictive accuracy is assessed using out-of-sample R^2, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), while SHapley Additive exPlanations (SHAP) are used to interpret the relative importance of the explanatory variables.

Table 7. Predictive Performance of Machine Learning Models

Performance Metric	Random Forest	XGBoost	LightGBM
Test R^2	−0.309	−0.327	−0.304
MAE	1.570	1.559	1.575
RMSE	2.387	2.403	2.382
Overall Ranking	2	3	1

Notes: Predictive performance was evaluated using the out-of-sample test dataset (2018–2020). Lower MAE and RMSE values indicate better predictive accuracy, whereas higher R^2 values indicate greater explanatory performance. Although all three algorithms exhibit relatively similar predictive performance, LightGBM achieves the lowest RMSE and the highest (least negative) test R^2, while XGBoost records the lowest MAE.

All three models yield negative out-of-sample R^2 values, indicating limited generalization performance relative to a simple mean-prediction benchmark over the 2018–2020 test period. This result warrants a cautious interpretation of the machine-learning component and suggests that the models should be viewed primarily as complementary tools for exploring nonlinear predictive structure and variable importance rather than as high-accuracy forecasting models. Instead, it is due to the large variety of international macroeconomic statistics, the relatively short prediction horizon, and the unprecedented structural disruptions that occurred in the post-pandemic period. As such, MAE and RMSE can serve as more appropriate measures for predictive performance in the current investigation.

Table 7 shows the relative predictive performance of three ensemble-learning algorithms used in this paper. In conclusion, the results suggest that Random Forest, XGBoost, and LightGBM achieve similar degrees of predictive accuracy, indicating that multiple types of machine-learning methods repeatedly identify the fundamental variables of Tourism Financial Resilience. Such strong similarities among the three algorithms add to the confidence that empirical findings are not determined by the specific property of one predictive model.

Among the three algorithms, LightGBM provides the most favorable relative performance according to RMSE and test R^2, although the differences across models are modest and all test R^2 values remain negative. LightGBM records the lowest RMSE (2.382) and the least negative R^2 (−0.304), whereas XGBoost achieves the lowest MAE (1.559). Accordingly, no model demonstrates uniformly superior out-of-sample predictive performance across all evaluation criteria.

Random Forest produces the second-best overall performance, recording an RMSE of 2.387 and a test R^2 of −0.309. The relatively small difference between Random Forest and LightGBM suggests that bootstrap aggregation provides stable predictions despite the considerable heterogeneity of the international panel dataset. By contrast, XGBoost achieves the lowest Mean Absolute Error (1.559), implying slightly better average prediction accuracy, but simultaneously records the highest RMSE and the lowest out-of-sample R^2 among the three algorithms. This pattern suggests that although XGBoost performs well for typical observations, it is comparatively less successful in predicting larger deviations associated with periods of elevated global uncertainty.

All three algorithms yield negative out-of-sample R^2 values, indicating limited generalization performance relative to a mean-prediction benchmark over the 2018–2020 test period. This finding warrants a cautious interpretation of the machine-learning results and highlights the difficulty of predicting Tourism Financial Resilience across a highly heterogeneous international panel. The test period includes the exceptional COVID-19 shock, while substantial cross-country variation in macroeconomic conditions, tourism dynamics, and global uncertainty further increases the complexity of the prediction task. Accordingly, the machine-learning models are interpreted primarily as complementary tools for examining nonlinear predictive patterns and model-based predictor importance rather than as high-accuracy forecasting models or substitutes for the panel econometric analysis.

In short, the relatively similar performance across Random Forest, XGBoost and LightGBM suggests that the machine-learning framework is robust enough to perform the follow-up explainability task on the data. Nonetheless, the predictive performance doesn't tell us anything about the variables motivating the model predictions itself. Accordingly, we first use SHapley Additive exPlanations (SHAP) for the next round of analysis to estimate the relative importance of each of the explanatory variables and to give an interpretable assessment of the nonlinear aspects affecting Tourism Financial Resilience.

Although Table 7 assesses the prediction performance of the machine-learning algorithms, predictive accuracy does not by itself disclose the relative contribution of each explanatory variable. SHapley Additive exPlanations (SHAP) was used to improve interpretability in the model. SHAP is an explainable artificial intelligence (XAI) approach that evaluates the mean contribution of each predictor to the predictions of a model using cooperative game theory. By decomposing prediction features into attributes for recognition, SHAP can identify the factors influencing Tourism Financial Resilience in a nonlinear machine learning model. The global feature importance ranking generated by the LightGBM model considering the mean absolute SHAP values was presented in Figure 4.

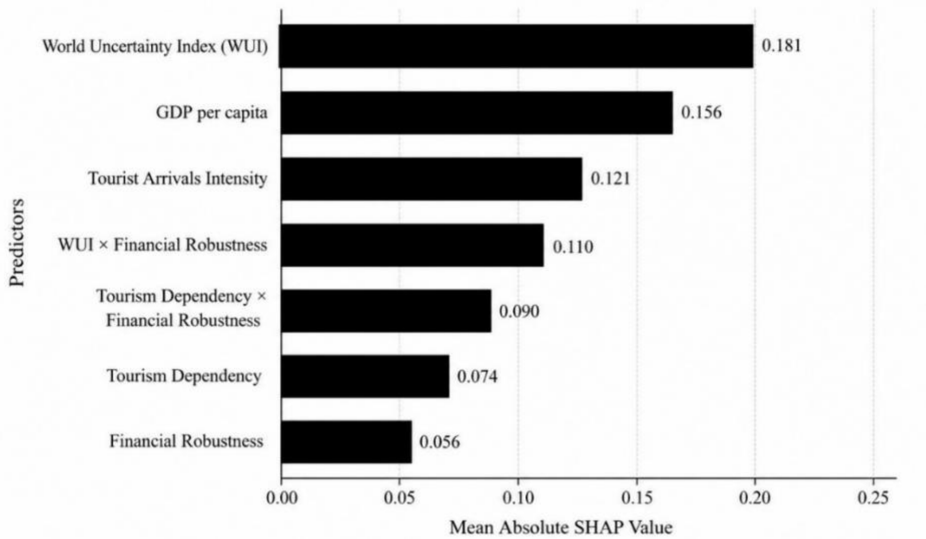

Figure 4. Global SHAP Feature Importance Based on the LightGBM Model

The World Uncertainty Index (WUI) (Figure 4) is the most influential predictor of Tourism Financial Resilience, exhibiting the highest mean absolute SHAP value among all explanatory variables. The main reason for the effect is that global uncertainty changes contribute the largest proportion to the variability in model predictions, which confirms the importance that external macroeconomic shocks have in determining the resilience of tourism across countries.

GDP per capita becomes the second most significant predictor (Tourist Arrivals Intensity follows), indicating that tourism-dependent economies' ability to adapt is highly dependent on both the level of economic development and the intensity of international tourism. While these variables were weakly statistically significant in certain econometric specifications, the SHAP analysis reveals that they contribute meaningfully to nonlinear prediction accuracy, highlighting the complementary insights provided by explainable machine-learning techniques.

The interaction variables (WUI × FR and TD × FR) occupy intermediate positions in the global importance ranking, indicating that the combined effects of uncertainty, financial robustness, and tourism dependency improve prediction performance but remain less influential than the direct effects of macroeconomic uncertainty. Finally, Tourism Dependency and Financial Robustness individually exhibit the lowest average SHAP values, implying that their predictive contribution depends largely on country-specific conditions and interactions with other explanatory variables rather than on universally strong marginal effects.

The SHAP feature importance analysis is highly consistent with the panel econometric results. Both approaches have found global uncertainty as the main driver behind Tourism Financial Resilience, as well as economic development and tourism intensity that support it. Thus, by showing that variables revealed through statistical inference also represent the most significant predictors in a nonlinear machine-learning framework, the explainable artificial intelligence analysis improves the robustness of the empirical results.

Overall, the explainable machine-learning results complement the panel econometric findings rather than replacing them. Significantly, econometric models reveal statistically significant averages and heterogeneous effects among resilience levels, while machine-learning approaches uncover nonlinear predictive structures and interactions among variables that might be hidden within traditional regression structures. Concordance of the two analytical approaches increases the empirical results' validity and the level of confidence in the proposed Tourism Financial Resilience framework.

6. Discussion and Conclusion

By integrating conventional panel econometric techniques and explainable machine learning, this study investigates the factors affecting Tourism Financial Resilience (TFR) in tourism-dependent economies under conditions of persistent global uncertainty. Inspired by the increasing vulnerability of tourism-dependent economies to financial, geopolitical, and macroeconomic shocks, this research presents a new Tourism Financial Resilience Index (TFRI), which is derived using Principal Component Analysis (PCA). While existing tourism resilience measures primarily focus on tourism recovery or destination performance, the revised index comprises both tourism dynamics and macro-financial stability to offer a more holistic analysis of countries' capacity to withstand, absorb, and recover from external disturbances.

Using an unbalanced panel dataset comprising 144 tourism-dependent countries and 1,533 country-year observations over the 2010–2020 period, the empirical analysis combined fixed-effects estimation with Driscoll–Kraay robust standard errors, Panel Quantile Regression, and three ensemble machine-learning algorithms (Random Forest, XGBoost, and LightGBM). This hybrid analytical framework enabled the simultaneous evaluation of average relationships, heterogeneous effects across different resilience levels, nonlinear prediction performance, and variable importance, thereby providing complementary evidence from both econometric inference and explainable artificial intelligence.

The empirical results have several key conclusions drawn. First, tourism dependency alone is not a statistically significant factor for Tourism Financial Resilience after controlling for macro-financial conditions. This indicates that economies dependent on tourism income are not inherently more resilient or more vulnerable. Rather, the resilience of tourism-dependent economies depends very much on macroeconomic and institutional conditions that impact their capacity to absorb external shocks. Thus, tourism specialization should not be perceived as either a structural advantage or a structural weakness in isolation.

Second, financial robustness does not have a statistically significant influence directly on Tourism Financial Resilience, nor does it also play a significant role in the enhancement of the relationship between tourism dependence and resilience. Despite strong external balances and adequate international reserves being considered fundamental to macroeconomic stability, the fact that financial fundamentals are inadequate to ensure resilient growth in a system of broad structural and institutional mechanisms is clear. This finding highlights the fact that financial resources are essential but not sufficient conditions in tourism-dependent economies to guarantee resilient response.

Third, global uncertainty emerges as the most consistently significant correlate of Tourism Financial Resilience across the empirical specifications. The fixed-effects results indicate a statistically significant negative association between global uncertainty and Tourism Financial Resilience, suggesting that higher levels of global uncertainty are associated with lower resilience in tourism-dependent economies. Moreover, the statistically significant interaction between global uncertainty and financial robustness indicates that the association between global uncertainty and Tourism Financial Resilience varies with countries' macro-financial conditions. Taken together, these findings are consistent with the broader theoretical perspectives of Dynamic Capabilities Theory and Complex Adaptive Systems Theory, which conceptualize resilience as reflecting not only exposure to external disturbances but also the capacity of economic systems to adapt to and absorb such disturbances.

More generally, these results are consistent with previous studies of tourism resilience, such as the analysis of Hall et al. (2022) and Briguglio et al. (2009) that underscore that macro-financial preparedness is a prerequisite for sustaining tourism systems to resist external shocks. Different from previous literature (that largely emphasized destination recovery or tourism performance), the present study shows that tourism financial resilience is jointly determined by tourism specialization, macro-financial conditions, and global uncertainty within the same empirical framework.

The Panel Quantile Regression analysis further confirms that the predictors of Tourism Financial Resilience are not entirely uniform among countries. Even though tourism dependency is a consistent positive predictor throughout the conditional distribution of resilience, the impact of global uncertainty is continuously negative. These results demonstrate an external uncertainty limitation on tourism financial resilience independent of countries' initial resilience levels, while the role of tourism activity is more pronounced when tourism activity is assessed at various segments instead of only at the conditional mean. Such heterogeneous results confirm that average regression estimates will likely distort important differences between resilience regimes. Hence, integrations of conventional panel econometrics with Panel Quantile Regression offer a better understanding of how tourism-dependent economies react to global uncertainty under a variety of resilience settings.

The econometric findings are further complemented by the machine-learning analysis, which provides additional evidence on nonlinear predictive associations and model-based variable importance. However, the negative out-of-sample R^2 values indicate limited generalization performance for Random Forest, XGBoost, and LightGBM over the 2018–2020 test period. Accordingly, the machine-learning results should be interpreted primarily as complementary evidence on nonlinear predictive structure rather than as evidence of strong forecasting accuracy. Within this framework, the SHAP feature-importance analysis identifies the World Uncertainty Index as the most influential predictor of Tourism Financial Resilience, followed by GDP per capita and tourist arrivals intensity. The prominence of global uncertainty in both the econometric and SHAP analyses provides complementary evidence of its relevance to Tourism Financial Resilience, although the two approaches address different analytical questions. Whereas the panel models estimate conditional statistical associations, SHAP values quantify the contribution of individual predictors to fitted model predictions and should not be interpreted as causal effects. Taken together, these findings demonstrate the value of combining panel econometric inference with explainable machine learning while maintaining a clear distinction between statistical association, model-based predictor importance, and predictive performance.

This study makes distinct theoretical, methodological, and empirical contributions to the tourism resilience literature. Theoretically, it conceptualizes Tourism Financial Resilience (TFR) as a multidimensional construct shaped by the interaction between tourism exposure, macro-financial shock-absorption capacity, and persistent global uncertainty. By integrating Dynamic Capabilities Theory, Complex Adaptive Systems Theory, and Financial Resilience Theory, the study extends conventional tourism resilience perspectives beyond destination recovery and tourism performance toward the broader adaptive capacity of tourism-dependent economies. Methodologically, the study develops a multidimensional Tourism Financial Resilience Index (TFRI) that jointly captures tourism performance and macroeconomic stability and combines fixed-effects panel estimation, Panel Quantile Regression, and explainable machine learning within a complementary analytical framework. This design enables the assessment of average and heterogeneous statistical associations while also examining nonlinear predictive patterns and model-based predictor importance. Empirically, the findings demonstrate that global uncertainty is a persistent adverse correlate of Tourism Financial Resilience and that the role of financial robustness varies across model specifications and resilience levels. Taken together, these contributions provide a more comprehensive framework for understanding how tourism-dependent economies respond to external shocks under conditions of persistent global uncertainty.

These findings also have important policy implications. For governments, the findings suggest that bolstering tourism resilience extends much further than expanding tourism activity. Macroeconomic stability, sound fiscal management, external reserve adequacy, institutional quality, as well as sound risk-governance mechanisms that can absorb global shocks, should guide policy. Tourism authorities can supplement destination development policies with crisis preparedness, diversification of tourism markets, digital transformation, or adaptive governance frameworks that render tourism systems more agile in the context of uncertain global dynamics. International organizations should persist in supporting resilience-oriented policies by promoting financial preparedness, institutional cooperation, and the establishment of data-driven early warning systems that would recognize newly identified vulnerabilities in a timely fashion before they escalate into systemic crises.

Overall, the result points towards the conclusion that improving tourism resilience involves much more than simply increasing tourism activity. It becomes necessary for sustainable tourism resilience to be developed through the combined development of macro-financial stability, adaptive institutional capacity, and effective policy responses to persistent global uncertainty. Thus, these should be combined with broader macroeconomic and financial resilience policies to improve countries' capacity to withstand future global shocks.

However, the study has some limitations. The empirical analysis is limited to the years 2010 to 2020 as internationally comparable tourism statistics are substantially less complete after 2020. While this restriction ensures data consistency, future research could expand the analysis when more comprehensive post-pandemic datasets are made available. Similarly, the developed Tourism Financial Resilience Index focuses primarily on tourism and macro-financial indicators, thus failing to explicitly incorporate institutional quality, digital transformation, climate vulnerability, or environmental sustainability. Perhaps bringing these dimensions into the fold will afford a deeper insight into resilience under increasingly complex global risks. A further limitation concerns the out-of-sample performance of the machine-learning models. All three algorithms yield negative test R^2 values for the 2018–2020 period, indicating limited generalization performance relative to the mean-prediction benchmark. Consequently, the machine-learning results should be interpreted primarily as complementary evidence on nonlinear predictive associations and model-based variable importance rather than as a forecasting framework with strong out-of-sample accuracy. Future research could reassess predictive performance using longer post-2020 samples, alternative validation windows, dynamic forecasting models, and causal machine-learning approaches as more internationally comparable tourism data become available. A further limitation concerns the construction of the TFRI. The first principal component explains 43.29% of the total variance, while inverse unemployment and inverse inflation exhibit relatively low loadings. Accordingly, the index should be interpreted as a parsimonious common resilience component rather than as a complete representation of all dimensions of tourism financial resilience.

In general, we show that the financial resilience of tourism-dependent economies is less about the degree of tourism specialization, rather, it is reflected in the capacity to handle continued global uncertainty with sound macroeconomic fundamentals, as well as adaptive economic structures. Given the ongoing dynamics of global tourism which are becoming more and more unstable globally with geopolitical tensions, financial instability, climate-related disruptions, and policy uncertainty, the construction of resilient tourism economies will depend on synergistic approaches that unify tourism development with macro-financial stability, institutional adaptability, and evidence-based policymaking. Therefore, this study proposes a multidimensional resilience index in the context of panel econometrics and explainable machine learning to provide a comprehensive analytical framework as an analytical guide to improve the insight into tourism resilience and contribute to a robust foundation for future empirical and policy-oriented research.

More broadly, the findings suggest that tourism resilience should not be understood solely in terms of the recovery of tourism activity following crises. Instead, Tourism Financial Resilience can be conceptualized as a multidimensional macro-financial capacity reflecting the interplay among tourism performance, financial shock-absorption capacity, adaptive economic structures, and persistent global uncertainty. From this perspective, the resilience of tourism-dependent economies depends not only on their ability to restore tourism activity after external disruptions but also on their capacity to maintain macro-financial stability and adapt to changing external conditions. By adopting this broader perspective, the study extends the conventional recovery-oriented understanding of tourism resilience toward a more integrated framework that emphasizes adaptation, shock absorption, and macro-financial preparedness under persistent global uncertainty.

DECLARATIONS

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