



Article

Enhancing Big Data Solutions in the Tourism Industry Economic Efficiency and Forecasts Indicators

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Abstract: The article examines scientific and methodological approaches to assessing and modeling the efficiency of the tourism industry based on Big Data. It substantiates mechanisms for quantitatively evaluating the impact of Big Data investments on profitability, integrating direct and indirect efficiency indicators, hybrid forecasting of tourism demand, DEA-based destination efficiency analysis, optimal resource allocation, and early risk detection. The KSBI index, KMTM resource allocation model, hybrid ARIMA + ML forecasting model, and IXK risk indicator are proposed as a methodological basis for managing the tourism industry in the digital economy.

Keywords: Big Data, tourism economy, efficiency assessment, modeling, KSBI, DEA, hybrid model, ARIMA, machine learning, resource allocation, risk management.

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1. Introduction

In the tourism economy, Big Data has emerged not only as a technological tool but also as a value-generating economic resource. Mechanisms such as dynamic pricing, hyper-personalized recommendations, and proactive resource allocation theoretically promise substantial economic benefits. However, in practice, tourism managers face a fundamental question: to what extent are these mechanisms truly effective, and how can the economic returns on Big Data investments be accurately measured? Conventional financial reporting alone cannot adequately answer this question, making a specialized scientific and methodological framework essential for evaluating Big Data-driven performance [1].

Research Objective. The primary objective of this study is to improve the scientific and methodological approaches for evaluating and modeling the efficiency of the tourism sector based on Big Data technologies. To achieve this objective, the study proposes the development of a hybrid economic-mathematical model for tourism demand forecasting, methodologies for assessing the efficiency of tourism destinations, and scientifically grounded mechanisms for optimal resource allocation and risk management within the national tourism ecosystem.[2]

Research Tasks. The study pursues the following tasks: to conduct a comparative analysis of the scientific and theoretical foundations of Big Data applications in tourism economics, as well as traditional and modern performance evaluation methods; to develop a Comprehensive Performance Evaluation Index (KSBI) based on the integration of direct and indirect economic indicators, including Customer Lifetime Value (CLV), Net Promoter Score (NPS), and brand reputation. [3]

Research Object. The object of the research is the tourism sector of the Republic of Uzbekistan and its digital ecosystem. It encompasses tourism service providers (including hotels, tour operators, transportation companies, and related enterprises), tourism destinations, the governmental regulatory system for tourism, and the integration processes between the national tourism market and international digital tourism platforms.[4]

Research Subject. The subject of the research comprises the economic, organizational, and managerial relationships arising from the implementation of Big Data technologies in the tourism industry. Within this framework, the study focuses on methodologies for evaluating sectoral efficiency, modeling tourism demand, and optimizing resource allocation.[5]

A notable paradox observed in practice is that although many large tourism companies invest heavily in Big Data technologies, they often fail to quantify the actual impact of these investments on business profitability. According to an MIT Sloan study, only 34% of the 245 surveyed tourism companies reported that they were able to accurately measure the effectiveness of Big Data initiatives within their own business context [6]. This finding clearly demonstrates the strategic necessity of developing robust methodological approaches for performance evaluation.

According to the approach proposed in this research, assessing the economic efficiency of Big Data requires the simultaneous resolution of three interrelated methodological challenges. First, an appropriate system of performance metrics must be established. Second, a methodology for collecting and processing empirical data based on these metrics must be developed. Third, predictive models should be constructed to support strategic decision-making using the measured indicators. Each of these methodological challenges presents distinct theoretical and practical difficulties, and comprehensive solutions have not yet been fully developed in the existing economic literature [7].

2. Methodology

In classical economics, efficiency has traditionally been assessed using financial and retrospective indicators such as Return on Investment (ROI), Return on Equity (ROE), and Economic Value Added (EVA) [8]. However, considering the specific characteristics of the service and tourism industries, non-parametric evaluation methods, particularly Data Envelopment Analysis (DEA), have become widely applied for measuring the efficiency of multi-criteria resource utilization [9]. This approach enables comparative evaluation of the efficiency of tourism destinations and hospitality enterprises operating with different combinations of inputs and outputs. Previous studies have demonstrated that investments in information technologies significantly improve organizational productivity while data-driven decision-making has become one of the principal drivers of business competitiveness [10]. Furthermore, contemporary performance evaluation increasingly incorporates not only direct financial outcomes but also indirect indicators, including Customer Lifetime Value (CLV) and Net Promoter Score (NPS), as essential measures of organizational performance [11].

Historically, methodologies for evaluating economic efficiency have evolved within two major schools of thought: parametric and non-parametric approaches. Parametric approaches—represented by indicators such as ROI, ROE, and EVA—are based on predefined functional forms and statistical distribution assumptions [12]. In contrast, non-parametric methods, including Data Envelopment Analysis and the Malmquist Productivity Index, do not require prior specification of the production function [13]. Figure 1. Both approaches possess distinct strengths and limitations; however, the emergence of Big Data technologies has significantly expanded their analytical capabilities.

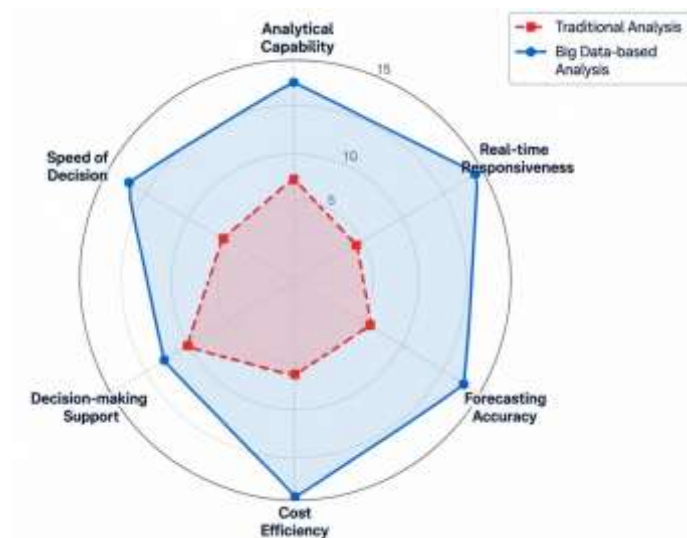


Figure 1. Comparative characteristics of traditional and Big Data-based performance evaluation methods (10-point scale).

As illustrated in Figure 1, Big Data-based evaluation methods substantially outperform traditional approaches in terms of real-time responsiveness (10 versus 3 points), forecasting capability (9 versus 4 points), and scalability (10 versus 4 points). Table 1. Traditional approaches maintain a relative advantage in cost efficiency because they do not require sophisticated information technology infrastructures. Nevertheless, this advantage is gradually diminishing in the digital economy. Once investments in Big Data infrastructure have been made, its cost efficiency improves as the scale of operations increases [14].

Table 1. Comparative Analysis of Traditional and Big Data-Based Methods for Evaluating Tourism Performance.

Evaluation Criteria	Traditional Methods	Modern Big Data-Based Methods
Data Type	Retrospective statistics; surveys; accounting reports	Real-time data streams (APIS, sensor data); social media; geolocation; transactional data
Time Horizon	Ex-post analysis; annual or quarterly reporting	Real-time and predictive analytics; minute-level updates
Direct Performance Measurement	ROI, ROA, EBITDA (financial indicators only)	Multidimensional indicators integrating financial, customer behavior, operational, and market performance
Indirect Performance Measurement	Rarely measured or assessed through expert judgment	Brand Value Index, NPS dynamics, Customer Lifetime Value (CLV), sentiment scores
Decision-Making Speed	Delayed (annual or quarterly cycles)	Operational (hourly/daily), tactical (weekly), and strategic (monthly)
Risk of Error	High, as statistical anomalies are often overlooked	Low, owing to real-time anomaly detection and compensation mechanisms
Scalability	Analytical complexity increases with data volume	Model accuracy improves as data volume increases (Big Data effect)
Key References	Copeland et al. Damodaran	Provost & Fawcett; Siegel

One of the principal methodological distinctions presented in Table 1 concerns the measurement of direct and indirect performance. Big Data-based evaluation methods enable the assessment of indirect economic performance-strategically important indicators that are generally invisible in conventional financial reporting [15]. The most significant of these indicators include Customer Lifetime Value (CLV), Customer Acquisition Cost (CAC), the Online Brand Reputation Index (OBRI), and the Net Promoter Score (NPS).

To integrate these dimensions, the author proposes the Comprehensive Performance Evaluation Index (KSBI), which combines direct and indirect performance components as follows:

$$KSBI = \lambda^1 \times E_{dir} + \lambda^2 \times E_{indir}, \quad 0 < \lambda^1, \lambda^2 < 1, \quad \lambda^1 + \lambda^2 = 1$$

Here: E_{dir} denotes the direct performance component, expressed as $f(\Delta RevPAR, \Delta Cost, \Delta Occ)$; E_{indir} denotes the indirect performance component, expressed as $f(\Delta CLV, \Delta NPS, \Delta Brand, \Delta MarketShare)$; λ^1 and λ^2 represent strategic weighting coefficients determined according to the enterprise's stage of development. During the growth stage, $\lambda^2 > \lambda^1$, whereas for well-established branded businesses, $\lambda^1 \geq \lambda^2$.

The interpretation of the index is as follows: $KSBI > 1.0$ - High performance; $0.7 \leq KSBI \leq 1.0$ - Satisfactory performance; $KSBI < 0.7$ Performance improvement is required.

The novelty of this index lies in its integration of relational performance indicators alongside traditional financial metrics within a unified evaluation framework. Customer Lifetime Value is particularly significant in the tourism sector because retaining an existing tourist is estimated to be five to seven times less expensive than acquiring a new customer [16]. Big Data technologies enable this indicator to be monitored continuously in real time and maintained at an optimal level.

The application of economic modeling in tourism is inherently complex and is primarily implemented in three interrelated areas: tourism demand forecasting, optimal resource allocation, and quantitative risk assessment. Each of these areas requires distinct methodological foundations and data resources. The present study argues that these three dimensions should be integrated into a single analytical framework, as treating them independently often leads to inefficient decision-making in practice [17].

3. Result and Discussion

Tourism Demand Forecasting Models. From the perspective of the historical development of econometric forecasting methods, ARIMA (AutoRegressive Integrated Moving Average) and its seasonal extension, SARIMA, have remained the most widely used models for forecasting tourism demand [18]. However, these classical models have a significant limitation: they rely solely on historical time-series data and are unable to incorporate external information sources such as search engine trends, social media sentiment indicators, and online booking dynamics. To overcome this limitation, the author proposes a hybrid forecasting approach.

The proposed hybrid framework combines an econometric-statistical component (SARIMA) with machine learning algorithms, including Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) neural networks. These components operate in parallel, after which their outputs are integrated using optimal weighting coefficients to produce the final forecast. Such an approach eliminates the trade-off between the interpretability of econometric models and the predictive accuracy of machine learning, thereby minimizing forecasting errors while preserving the economic meaning of the model [19].

The mathematical formulation of the proposed hybrid forecasting model is expressed as follows

$$\hat{Y}_{gibrid}(t) = w_{eco} \times \hat{Y}_{SARIMA}(t) + w_{ml} \times \hat{Y}_{ML}(t) + w_{bd} \times BD(t)$$

where: $\hat{Y}_{SARIMA,t}$ denotes the forecast generated by the SARIMA model; $\hat{Y}_{ML,t}$ represents the forecast produced by the machine learning model; BD_t denotes the real-time Big Data component, including the Google Trends index, online booking intensity, and social media sentiment indicators; w_{eco} , w_{ML} , and w_{BD} are the weighting coefficients assigned to each forecasting component, satisfying the following constraint: $w_{eco} + w_{ML} + w_{BD} = 1$.

The Figure 2. weighting coefficients are calibrated through a cross-validation procedure using the available training dataset, ensuring that the hybrid model achieves the optimal balance between econometric interpretability, machine learning accuracy, and real-time information extracted from Big Data sources.

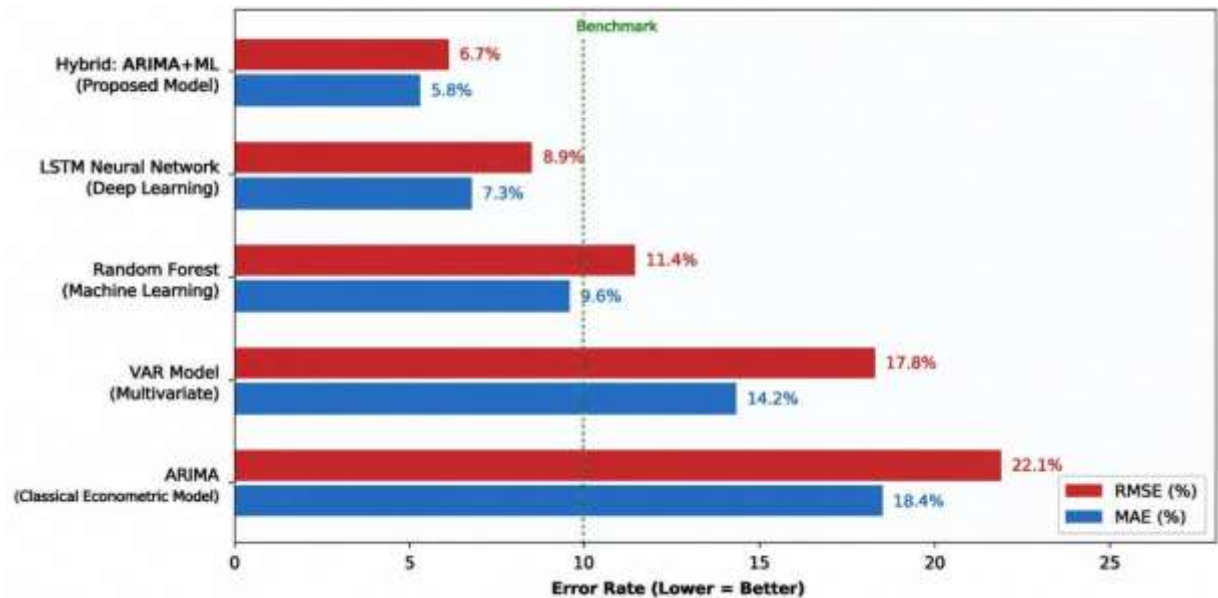


Figure 2. Comparison of the Forecasting Accuracy of Tourism Demand Models (MAE and RMSE, %, Test Dataset: 2022-2026).

Figure 2 clearly demonstrates the results of the comparative analysis. The hybrid model proposed by the author achieved a Mean Absolute Error (MAE) of 5.8% and a Root Mean Square Error (RMSE) of 6.7%, representing improvements of approximately 3.2 and 3.3 times, respectively, compared with the conventional ARIMA model. More importantly, the forecasting error of the hybrid model remains well below the 10% threshold, which is generally considered acceptable for practical forecasting applications.

The Figure 3. Random Forest and LSTM models also exhibited relatively high predictive performance; however, their accuracy was slightly lower than that of the proposed hybrid model. This can be attributed to their inability to fully incorporate the Big Data (BD) component, including real-time external signals such as search trends, online booking dynamics, and sentiment indicators, which provide valuable economic information for improving forecasting performance.

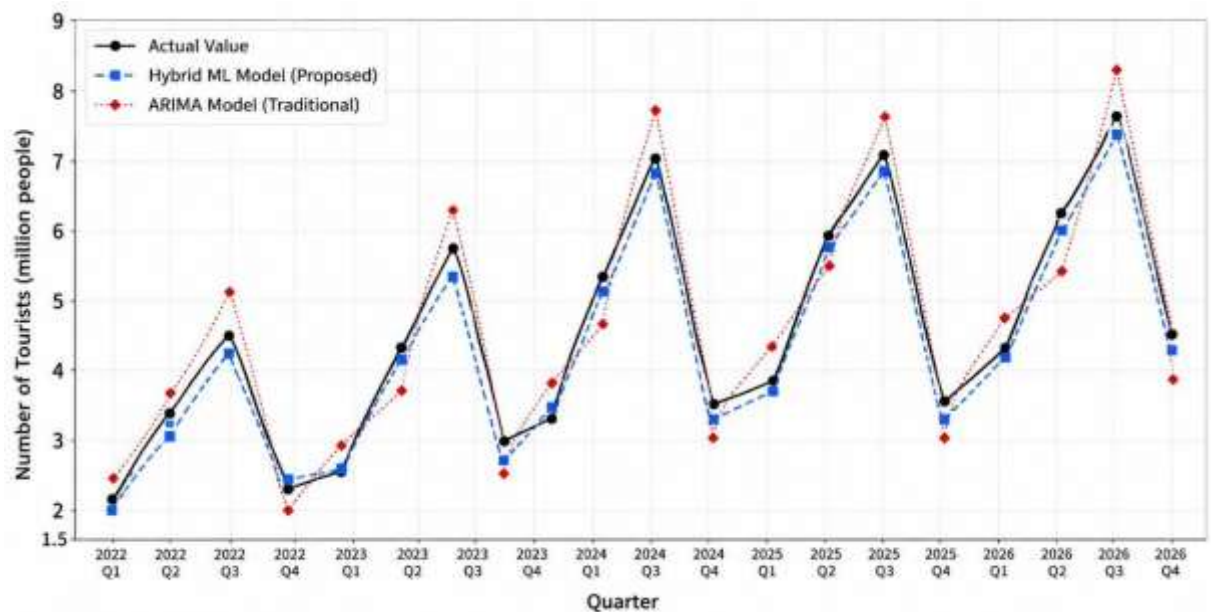


Figure 3. Forecast of Tourism Flows: Comparison of the Hybrid Machine Learning Model and the ARIMA Model (Central Asia, 2022-2026).

Figure 3 illustrates that the forecasts generated by the proposed hybrid model closely follow the actual tourism flows, particularly during seasonal peak periods (summer quarters), where the difference between the hybrid model and the conventional ARIMA model becomes especially evident. For instance, in the third quarter of 2023, the actual tourist flow reached 5.8 million visitors. The hybrid model predicted 5.5 million visitors, corresponding to a forecasting error of -5.2%, whereas the ARIMA model forecasted 6.3 million visitors, resulting in an error of +8.6%.

From a practical economic perspective, more accurate demand forecasts enable more efficient planning of hotel capacity and tourism infrastructure. Consequently, improved forecasting accuracy can increase tourism revenues by approximately 7-9% during seasonal peak periods through more effective allocation and utilization of available resources [20].

DEA Methodology and Relative Efficiency Analysis. To evaluate the relative efficiency of tourism destinations, the study adopts Data Envelopment Analysis (DEA) as the most appropriate methodological framework. Originally developed by Charnes, Cooper, and Rhodes [21], DEA enables the comparison of the relative efficiency of Decision-Making Units when multiple input and output variables are involved.

Within the tourism sector, DMUs are represented by tourism destinations or tourism enterprises. The principal input variables include investment, marketing expenditure, infrastructure capacity, and the number of employees, whereas the output variables comprise the number of tourists, tourism revenue, hotel occupancy rates, and the customer satisfaction index [22].

The DEA optimization problem is formulated as follows:

$$\max \theta_k = \sum_r u_r y_{rk} / \sum_i v_i x_{ik}$$

where: θ_k denotes the efficiency score of the k -th DMU ($0 \leq \theta_k \leq 1$); y_{rk} represents the r -th output of the k -th DMU; x_{ik} denotes the i -th input of the k -th DMU; u_r and v_i are the optimization weights assigned to output and input variables, respectively.

The optimization is subject to the following constraints: $\theta_j \leq 1, \forall j \in \{1, \dots, n\}, u_r, v_i \geq \epsilon > 0$.

The Figure 4. DEA model provides a robust non-parametric framework for benchmarking tourism destinations by identifying the most efficient units and quantifying the efficiency gaps of the remaining destinations relative to the best-performing benchmarks.

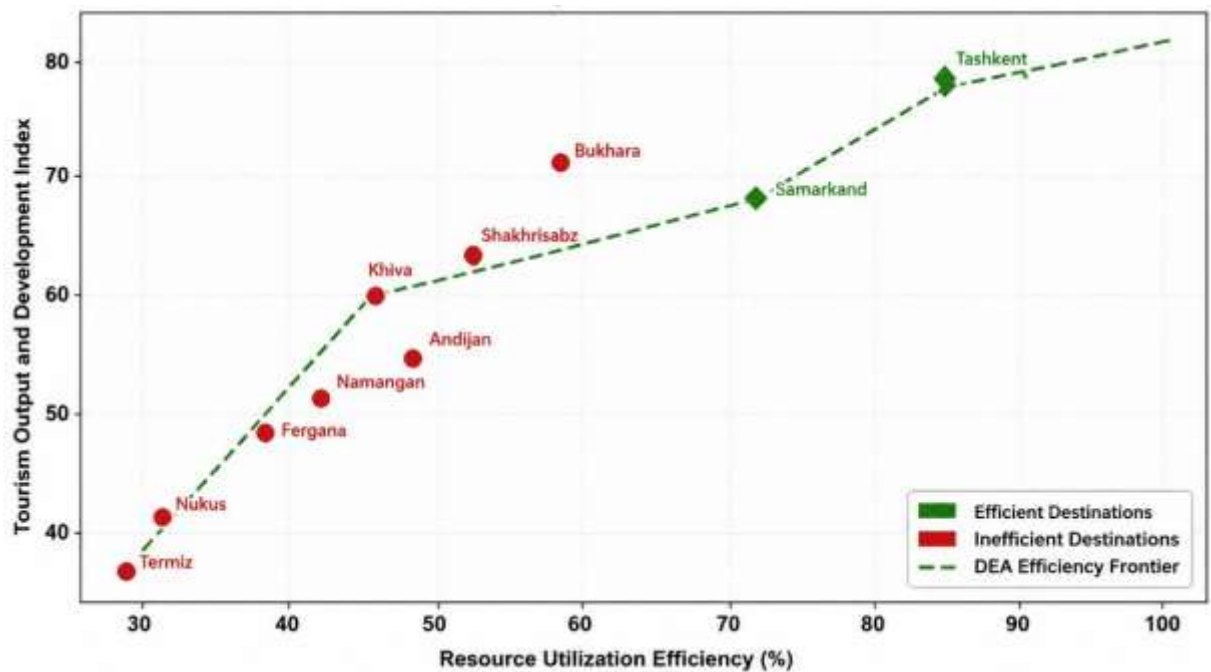


Figure 4. DEA Efficiency Analysis of Tourism Destinations in Uzbekistan (Based on 2025-2026 Data).

Figure 4 presents the results of the DEA analysis of tourism destinations in Uzbekistan. Tashkent and Samarkand are identified as the only efficient destinations located on the DEA efficiency frontier, serving as benchmark reference points for other destinations. Historical destinations such as Khiva, Bukhara, and Shakhrisabz are positioned below the efficiency frontier in terms of resource utilization efficiency.

This result indicates that these destinations have the potential to generate comparable levels of tourism revenue while utilizing fewer resources. In other words, there is significant potential for improving efficiency through the implementation of Big Data technologies and digital management tools, which can enhance resource utilization and operational decision-making processes [23].

Optimal Resource Allocation Models. The problem of optimal resource allocation in the tourism economy is addressed through the integration of Operations Research methods and economic optimization approaches. The essence of this problem is to determine how limited resources including human resources, transportation capacity, and financial investments should be distributed among destinations or service segments in order to achieve maximum economic efficiency [24].

The author proposes a Multi-Objective Resource Allocation Model (KMTM), which solves the following optimization problem:

$$\max Z = \sum_j (\alpha_j \times R_j(x_j) - \beta_j \times C_j(x_j))$$

where: Z represents the objective function (overall economic value of the tourism system); $R_j(x_j)$ denotes the revenue function obtained from allocating x_j resources to the j -th segment; $C_j(x_j)$ represents the cost function associated with allocating x_j resources to the j -th segment; α_j and β_j are the weighting coefficients of revenue and cost components for the j -th segment. The model is subject to the following constraints: $\sum_j x_j \leq X_{\max}$, $x_j \geq 0$ where $X_{\max}$ represents the total available resource capacity.

The Big Data component $BD(t)$ continuously updates the parameters of the revenue function $R_j(x_j)$ in real time. A key distinction between this model and traditional resource allocation approaches is that the revenue function $R_j(x_j)$ is not static but dynamically adjusted based on real-time Big Data inputs. For example, if Google Trends data indicate a significant increase in search activity for the Samarkand destination, the model automatically recommends increasing marketing resources allocated to this destination.

A similar data-driven approach was implemented by the Singapore Tourism Board in 2022, resulting in a reported 28% improvement in the efficiency of marketing expenditure allocation [25].

Risk Management Models. The tourism industry is exposed to a wide range of systemic risks, including economic cycles, political instability, epidemics, natural disasters, and exchange rate fluctuations, all of which directly influence tourist flows [26]. Traditional risk management approaches have primarily relied on insurance mechanisms and diversification strategies.

Figure 5. However, Big Data technologies provide new opportunities for proactive risk management through the development of early warning systems and real-time risk monitoring mechanisms. By analyzing large-scale data streams, including travel behavior patterns, online discussions, booking trends, and social sentiment indicators, tourism organizations can identify emerging risks at an early stage and implement preventive measures before significant economic losses occur.

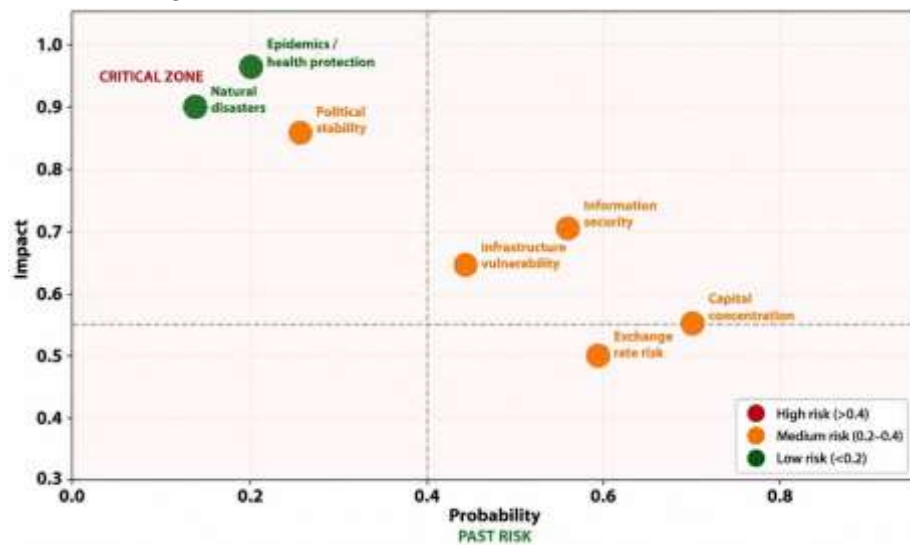


Figure 5. Risk Map of the Tourism Industry (Probability × Impact Matrix).

The risk matrix presented in Figure 5 identifies epidemics/health-related threats and natural disasters as the most critical risk categories for the tourism sector. The impact level of epidemic and health-related risks is estimated at 0.95, with a probability level of 0.20, while natural disasters demonstrate an impact level of 0.90 and a probability level of 0.15. Although these risks occur relatively rarely, their consequences can be extremely severe when they materialize, as clearly demonstrated by the COVID-19 pandemic in 2020.

The medium-impact risk zone includes exchange rate fluctuations (impact: 0.50, probability: 0.60) and infrastructure vulnerabilities (impact: 0.65, probability: 0.45). Big Data technologies enable continuous monitoring of early warning signals associated with these risks. For example, a sudden increase in epidemic-related terms within travel-related online discussions may serve as an indicator of declining booking demand, allowing tourism organizations to forecast potential disruptions in advance [27].

To quantitatively assess tourism-related risks, the author proposes the following **Integrated Risk Indicator (IXK)**:

$$IXK = \sum_{k=1}^K (p_k \times i_k \times c_k), \quad k = 1, 2, \dots, K$$

where: p_k represents the probability of occurrence of the k -th risk event ($0 \leq p_k \leq 1$); i_k denotes the economic impact intensity of the k -th risk, measured on a normalized scale from 0 to 1; c_k represents the correlation coefficient reflecting the amplification effect of the k -th risk when combined with other risks ($c_k \geq 1$). The interpretation of the IXK indicator is defined as follows: $IXK < 0.15$ low-risk zone; $0.15 \leq IXK \leq 0.35$ medium-risk zone; $IXK > 0.35$ critical-risk zone.

Table 2. Based on real-time Big Data inputs $BD(t)$, the probability coefficient p_k is recalculated on a daily basis, allowing the risk assessment system to dynamically reflect changes in the external environment and support proactive managerial decision-making.

Table 2. Comparative Analysis of Economic Modelling Methods in the Tourism Industry[28].

Model type	Economic essence	Advantages	Limitations
ARIMA / SARIMA (econometric model)	Time series analysis with consideration of seasonal components	High interpretability; strong statistical foundation	Based on assumptions of linear relationships; difficult integration with Big Data
VAR model (multivariate model)	Modelling a system of interrelated macroeconomic variables	Enables causality analysis	Involves many parameters; becomes slower when processing large datasets
DEA (Data Envelopment Analysis)	Evaluation of relative efficiency based on multiple input and output variables	Non-parametric approach; allows integration of indicators with different measurement units	No statistical significance testing; sensitive to outliers
Random Forest / GBM (machine learning models)	Ensemble tree-based models for identifying nonlinear relationships	High predictive accuracy; resistant to overfitting	Difficult interpretation ("black box" nature); requires significant computational resources
LSTM neural network (deep learning)	Recurrent neural network that learns temporal dependencies	Provides the highest accuracy for complex time series	Requires large training datasets; complex hyperparameter tuning
Hybrid ARIMA + ML model (author's proposal)	Combines econometric interpretability with machine learning accuracy and incorporates the Big Data component	Accuracy + interpretability; preserves economic meaning	Requires two-stage calibration and domain expertise

The comparative analysis presented in Table 2 demonstrates that each modelling method has its own specific economic essence, advantages, and limitations, and none of them can serve as a universal solution independently.[29]

The hybrid model proposed by the author is aimed at addressing this challenge by combining the economic interpretability of ARIMA, the predictive accuracy of machine learning, and the real-time information capabilities of Big Data, thereby creating a comprehensive analytical framework.[30]

4. Conclusion

The study demonstrates that the integration of Big Data solutions into the tourism industry creates significant opportunities for improving economic efficiency, strengthening evidence-based management, and increasing the accuracy of forecasting indicators. The growing volume of digital information generated through online bookings, hotel reservation systems, mobile applications, electronic payments, social media platforms, search engines, transportation systems, and destination-management platforms provides tourism organizations with a substantially broader information base than

traditional statistical approaches. When appropriately collected, processed, and analyzed, these data can be transformed into practical information for evaluating tourism demand, identifying market trends, optimizing resource allocation, and supporting strategic decision-making. The analysis indicates that Big Data technologies are particularly valuable for forecasting tourism-related indicators because they make it possible to incorporate both historical statistical information and real-time or high-frequency digital signals. Traditional forecasting models generally rely on periodically collected historical observations, whereas Big Data-based approaches can additionally consider online search behavior, booking dynamics, consumer reviews, mobility patterns, digital transactions, and other rapidly changing indicators. The combination of these sources improves the ability of tourism enterprises and public authorities to identify changes in consumer behavior at an earlier stage and adjust operational and strategic decisions accordingly. Economic efficiency in the tourism industry should also be considered as a multidimensional concept. It is not limited to increasing tourist arrivals or revenues but includes the effective utilization of accommodation capacity, transportation infrastructure, labor resources, marketing expenditures, investment, and digital technologies. Big Data analytics can contribute to this process by identifying inefficient resource allocation, estimating demand fluctuations, segmenting tourists according to behavioral characteristics, and supporting differentiated pricing and marketing strategies. In particular, predictive analytics and revenue-management techniques allow tourism businesses to adapt prices, capacity, promotional activities, and service offerings to expected demand conditions.

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