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APPLICATION OF ARTIFICIAL INTELLIGENCE ALGORITHMS IN MODELING ECONOMIC PROCESSES IN TOURISM

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Abstract. Tourism is one of the most dynamic sectors of the economy, but its key indicators — tourist flows, hotel occupancy, prices and revenues — depend on seasonality, prices, exchange rates and sudden external shocks. Traditional econometric models describe such processes only partly. This article examines the use of artificial intelligence (AI) algorithms for modeling economic processes in tourism. A five-stage framework is proposed: data collection, data preparation, AI modeling, model evaluation and decision support, with a feedback loop for regular retraining. The main tasks solved by AI in tourism are classified: demand forecasting, tourist segmentation, dynamic pricing and recommendation. A computational experiment on a synthetic monthly series of tourist arrivals with trend, seasonality and a crisis shock compares a seasonal naive method, linear regression, random forest, gradient boosting and a neural network. Gradient boosting gave the lowest forecast error (MAPE 4.3 %), while the regression model gave 6.6 % and the naive method 14.9 %. The results show that AI algorithms can improve the accuracy of planning in the tourism sector when combined with well-prepared data and correct evaluation.

Keywords: tourism economics, artificial intelligence, machine learning, demand forecasting, gradient boosting, neural network, modeling.

1. Introduction

Tourism creates income, jobs and foreign currency inflows, and it develops related sectors such as transport, trade and services. Managing this sector requires reliable forecasts of tourist flows, occupancy, prices and revenues. Errors in such forecasts lead to idle hotel rooms and transport capacity in some periods and to shortages in others [1].

Economic processes in tourism are difficult to model. Demand has strong seasonality, depends on incomes, prices and exchange rates, and reacts sharply to external shocks such as pandemics, crises and changes in visa rules. Traditional time-series and econometric models assume mostly linear relationships and often lose accuracy when these conditions change [1, 5].

Artificial intelligence methods — machine learning and neural networks — learn complex nonlinear relationships directly from data and can use many sources at once, including booking systems and online search queries [2, 8]. The development of smart tourism has made such data widely available [7]. The aim of this work is to propose a framework for applying AI algorithms to the modeling of economic processes in tourism and to compare AI models with traditional methods in a demand forecasting task.

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2. Materials and methods

Framework. The proposed framework (Figure 1) consists of five stages connected by a feedback loop. Data from official statistics, accommodation and booking systems, online searches, prices, exchange rates and calendars of events are cleaned and turned into features. AI models are trained on these features, evaluated against traditional baselines, and the best model is used for decisions. New data regularly return to the start of the cycle so that the models are retrained.

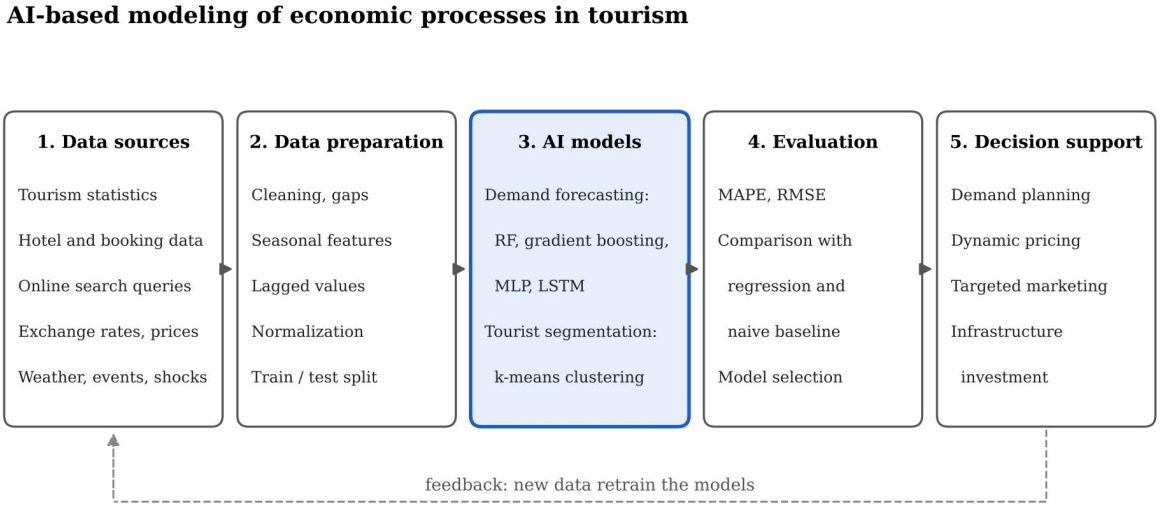


Figure 1. Framework for AI-based modeling of economic processes in tourism.

Tasks and algorithms. The main economic tasks in tourism and suitable AI algorithms are summarized in Table 1.

Table 1. Economic tasks in tourism and AI algorithms

Task	Economic question	AI algorithms	Result for management
Demand forecasting	How many tourists will come next month or season?	Random forest, gradient boosting, MLP, LSTM [2–4, 6]	Planning of hotel, transport and staff capacity
Tourist segmentation	Which groups of tourists exist and what do they spend on?	k-means and other clustering methods	Targeted marketing and tour products
Dynamic pricing	What price maximizes revenue at the given demand?	Demand models combined with optimization, reinforcement learning	Higher occupancy and revenue
Recommendation	Which destinations and services suit a given tourist?	Collaborative filtering, neural recommenders	Higher sales per tourist
Sentiment analysis	How do tourists evaluate services?	Natural language processing of reviews	Quality improvement

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Computational experiment. To compare methods, a synthetic monthly series of tourist arrivals for 2015–2024 (120 months) was generated. It contains an upward trend of about 0.9 % per month, a seasonal profile with peaks in May and September, random noise of about 5 % and a crisis shock from April 2020 to March 2021 with gradual recovery. Synthetic data were used so that the true structure of the series is known; the figures below therefore describe the methods, not real tourist flows.

The data for 2015–2022 were used for training and the 24 months of 2023–2024 for testing. The AI models predict the year-over-year growth rate of arrivals from its values in the previous 12 months, the month of the year and an indicator of the crisis period; the forecast level is then obtained as:

$$\hat{y}_t = y_{t-12} \cdot e^{\hat{g}_t}, \qquad g_t = \ln y_t - \ln y_{t-12}$$

Five methods were compared: a seasonal naive method (the value of the same month a year earlier), linear regression with trend, monthly dummy variables and a crisis indicator, random forest [4], gradient boosting [6] and a multilayer perceptron (MLP) neural network. Forecasts were made one month ahead. Accuracy was measured by the mean absolute percentage error:

$$\mathrm{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$

and by the root mean square error (RMSE). The experiment was implemented in Python with the scikit-learn library.

3. Results

The forecast accuracy of the five methods on the test period is shown in Table 2.

Table 2. Forecast accuracy on the test period (2023–2024, synthetic data)

Method	Type	MAPE, %	RMSE, thousand tourists
Gradient boosting	AI (ensemble of trees)	4.3	15.5
Random forest	AI (ensemble of trees)	4.8	16.3
Neural network (MLP)	AI (neural network)	6.0	19.6
Linear regression	Traditional econometric	6.6	19.1
Seasonal naive	Baseline	14.9	46.4

Gradient boosting gave the most accurate forecast: its error was about one third lower than that of linear regression and more than three times lower than that of the naive method. Random forest was close to it. The neural network was more accurate than regression in percentage terms but not in RMSE; with only about 70 training months, a neural network has too little data to show its full advantage.

Figure 2 compares the actual series with the forecasts of gradient boosting and regression. Gradient boosting follows the seasonal peaks and troughs of 2023–2024 more closely, while regression, which assumes the same seasonal pattern every year, misses the size of several peaks.

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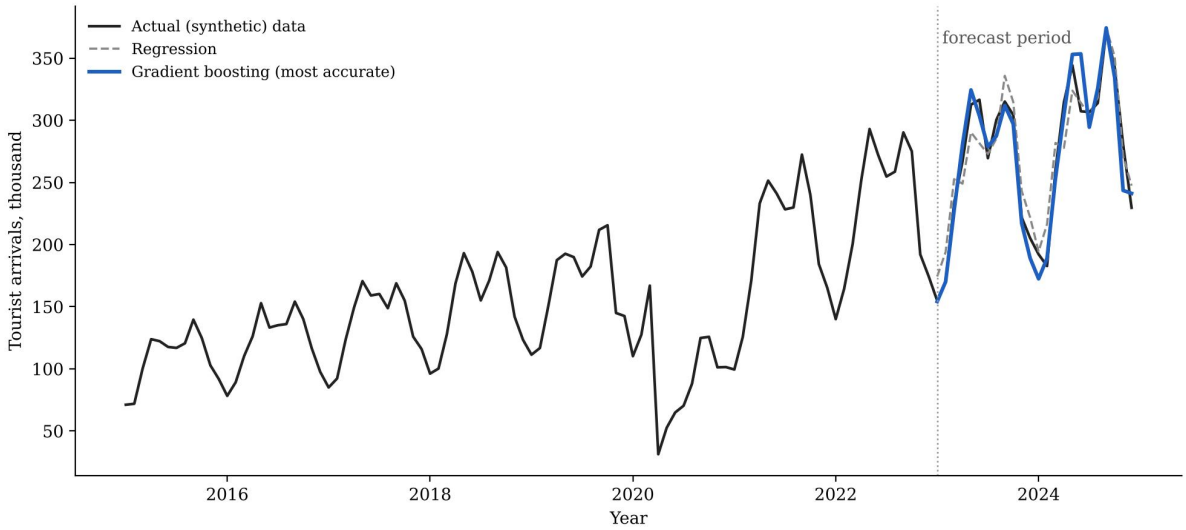


Figure 2. Actual (synthetic) tourist arrivals and one-month-ahead forecasts for 2023–2024.

The naive method failed because the test year differs from the previous one by the steady growth after the crisis. This illustrates a key advantage of AI models: they learn how growth itself changes and adapt to the recovery phase.

4. Discussion

The experiment confirms the findings of earlier studies that machine learning and deep learning models can outperform traditional methods in tourism demand forecasting [2, 8]. Tree ensembles are especially practical: they work well on small and medium data sets, need little tuning and show which features matter most, which helps economists interpret the results.

At the same time, AI does not replace economic analysis. Models trained on data before a crisis cannot foresee a new shock; this is why the crisis indicator and regular retraining in the feedback loop of the framework are necessary. Data quality is the main limitation: monthly official statistics are short series, while richer sources such as booking platforms and online searches must be collected and cleaned. For neural networks, including LSTM [3], longer series or data from many regions are needed.

For the tourism sector of Uzbekistan, the proposed framework can be applied by regional tourism administrations, hotels and tour operators to forecast seasonal demand, plan capacity and set prices. Further work will test the models on real regional data and add external factors such as exchange rates, flight schedules and online search indices.

5. Conclusion

A five-stage framework for applying artificial intelligence algorithms to the modeling of economic processes in tourism was proposed, and the main economic tasks with suitable algorithms were classified. In a computational experiment on synthetic data with trend, seasonality and a crisis shock, gradient boosting reduced the forecast error to 4.3 % MAPE, compared with 6.6 % for linear regression and 14.9 % for the seasonal naive method. AI algorithms are therefore an effective tool for forecasting and planning in tourism, provided that they are combined with high-quality data, correct evaluation and regular retraining.

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