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# Adaptive Neural Network Models for Tourism Preference Prediction: A Case Study in Serres

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This study presents the development of a tourist preference prediction system for the Municipality of Serres, based on data collected from visitor questionnaires. The system utilizes 14 neural networks, one for each potential destination or activity, to predict the likelihood of new visitors engaging with them. The models consist of four hidden layers with 16 neurons each, employing ReLU activation functions, and a sigmoid output layer for probability predictions. The binary_crossentropy function is used for error estimation. Categorical data, such as gender, country of origin, and mode of transport, are encoded using one-hot encoding, and the training process is implemented with the TensorFlow/Keras library. To deploy the system, an API built with FastAPI provides predictions based on visitor data. Additionally, users can provide feedback on actual visits or activities, enabling the retraining of models to enhance prediction accuracy. This dynamic system adapts to user input, improving over time.

**Keywords:**
tourism preference prediction,
neural networks,
FastAPI,
ReLU,
dynamic systems

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## 1 Introduction

Tourism is an important economic sector that has a big impact on sustainability and regional development. However, as global tourism patterns evolve due to shifting traveler preferences, destinations face increasing challenges in maintaining competitiveness and ensuring visitor satisfaction, (Xiang & Fesenmaier, 2016). In order to improve visitor experiences and allocate available resources as efficiently as possible, data-driven methods have become essential in understanding and predicting visitor preferences, (Claveria, Monte, & Torra, 2015), (Law, Li, Fong, & Han, 2019). In this context, machine learning techniques, particularly artificial neural networks, offer promising solutions for personalizing recommendations and improving tourism management strategies, (Shrestha, Wenan, Shrestha, Rajkarnikar, & Jeong, 2024), (Azevedo, Fernandes, Teixeira, & Ferreira, 2011).

The municipality of Serres is a location rich in historical, cultural and natural attractions, that each year attracts thousands of tourists. However, due to the dynamic nature of visitor preferences and the continuously evolving tourism landscape, modern tools are required to sustain visitor interest and enhance service effectiveness, (Çuhadar, Cogurcu, & Kukrer, 2014). While surveys and statistical analyses remain valuable, they are unable to fully capture the complexity of tourism patterns on their own, (Palmer, Montaño, & Sesé, 2006). In order to overcome these limitations, this research proposes a tourism preferences prediction system, that utilizes neural networks to forecast the destinations and activities most suitable for each individual visitor, based on their unique characteristics and preferences.

In this study, a tourism preferences prediction system is created, which provides personalized suggestions for activities and destinations based on each visitor's individual interests. To achieve this, the system utilizes user-inputted data to tailor recommendations more effectively. When users access the system via the Tourism Prediction System, they are prompted to complete a questionnaire that collects important data such as gender, age, means of transportation (car, public transportation, other), travel style (solo, family, friends) and travel period (Winter, Spring, Summer, Autumn). Additionally, users are asked to rate various aspects of interest on a scale from 1 to 5, including nature, history, culture, gastronomy, entertainment and motor sports. Using this information, the system makes tailored suggestions, aiming to improve the visitor's experience by aligning recommended activities to personal preferences.

To further support decision-making, users can access the Tourism Statistics Portal, which provides descriptive analytics on visitor trends. The platform offers insights into gender distribution among visitors, the most popular travel periods, preferred modes of travel (individual, group, or family), and the primary means of transportation used. By analyzing these factors, stakeholders and visitors alike gain a clearer understanding of tourism patterns in Serres. Additionally, the system incorporates a feedback mechanism, allowing visitors to rate and review the recommended locations after their visit. This feedback not only validates the initial recommendations but also enables the system to refine its predictive accuracy through continuous retraining. As a result, the algorithm evolves dynamically, improving future recommendations and ensuring greater alignment with visitor expectations.

The rest of the paper is structured as follows: Section 2 describes the employed methodology and Section 3 presents the results. Finally, Section 4 provides the conclusions.

## 2 Methodology

This section presents the methodology followed for the development of the tourism preference prediction system. The process began with the creation of an initial dataset through structured questionnaires distributed to tourists. Data collection was conducted through Google Forms, allowing responses to be efficiently collected from a diverse group of travelers.

The initial dataset consists of 600 samples with 11 features each. These features include gender, age, means of transportation (car, public transportation, other), travel style (solo, family, friends), and travel period (Winter, Spring, Summer, Autumn). Additionally, the dataset contains ratings on a scale from 1 to 5 for various aspects of interest, including nature-related activities, history, culture, gastronomy, entertainment, and motor sports. Subsequently, due to the structure of the algorithm, which undergoes continuous retraining, the dataset is enriched with an additional number of samples collected from tourists who complete the questionnaire. The data was processed anonymously, respecting the privacy of all tourists.

Based on this dataset, a neural network-based algorithm was developed to generate personalized recommendations. The system utilizes 14 neural networks, one for each potential destination or activity, to predict the likelihood of new visitors engaging with them. Each model consists of four hidden layers with 16 neurons per layer, employing ReLU activation functions and a sigmoid output layer for probability predictions, (Goodfellow, Bengio, & Courville, 2016), (Rasamoelina, Adjailia, & Sincak, 2020). The binary_crossentropy function is used for error estimation. Categorical data, such as gender, means of transportation, travel style and travel period, are encoded using one-hot encoding, ensuring compatibility with the neural network architecture. The training process is conducted using the TensorFlow/Keras library, which provides efficient deep learning model development and optimization, (Chollet, 2017).

To make predictions accessible and user-friendly, the system is deployed through an API built with FastAPI. This allows visitors to receive real-time recommendations based on their provided information. The recommendations include local gastronomy options such as souvlaki, bougatsa, and akanes, as well as notable attractions like the Xenakis Museum, the Old Metropolis, Freedom Square, and the Serres Circuit. Additionally, other recommended locations include Agios Prodromos, the Acropolis of Serres, the Valley of Agii Anargyri, Lailias, the Historic Center and pedestrian streets, Agios Ioannis, and the Archaeological Museum. The probability scores generated by the neural networks reflect the likelihood that a user will engage with a particular destination based on their input preferences. These scores are computed using a sigmoid activation function in the final layer, producing values between 0 and 1. The higher the probability score, the stronger the match between the user's preferences and the destination's attributes.

Furthermore, the system incorporates a feedback mechanism where users can rate their experiences after visiting recommended locations. This feedback is integrated into the model, enabling retraining and continuous optimization of prediction accuracy. The dynamic nature of this system ensures it evolves over time, improving the relevance and precision of its recommendations.

# 3 Results

The tourism preference prediction system begins with a structured questionnaire (See Figure. 1), where users provide demographic and travel-related data. As shown in the image, users input their age, gender, travel style (solo, family, or friends), mode of transportation, and travel period. Additionally, they rate their interests in nature-related activities, history, culture, gastronomy, entertainment, and motor sports on a scale from 1 to 5. This structured input enables the system to generate personalized recommendations.

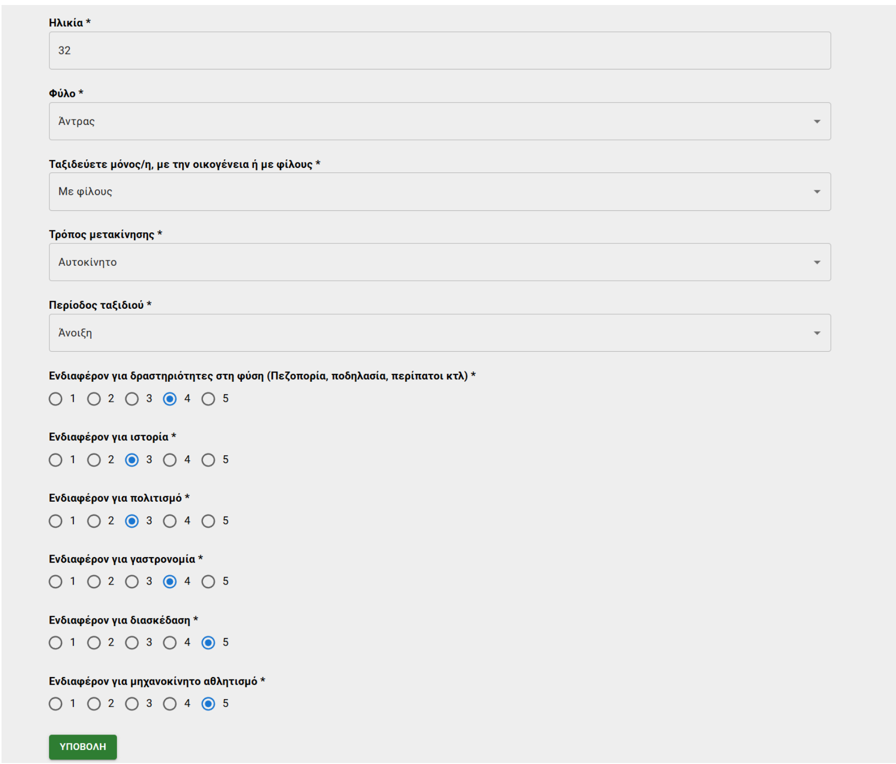


**Figure 1: Questionnaire**

Source: Own

After completing the questionnaire, the system processes the data and provides customized recommendations. As seen in the results interface, the AI model suggests destinations and activities with corresponding relevance scores. In this example, suggested locations include Agios Prodromos, the Xenakis Museum, Bougatsa, Freedom Square, and Souvlaki. These recommendations are based on the user's preferences and previous visitor trends. Five out of fourteen possible destinations are selected to ensure that users receive a manageable and meaningful set of recommendations without overwhelming them with too many choices.

Each recommendation is associated with a confidence score, indicating the likelihood that the suggested location or experience aligns with the user's preferences. For example, in the results displayed, Agios Prodromos has a 72.35% probability, making it the most relevant suggestion. Xenakis Museum follows with a 60.35% probability, indicating a strong cultural interest. Bougatsa (44.82%) and Souvlaki (25.28%) suggest a moderate preference for local gastronomy. Freedom Square (36.87%) is also highlighted as a significant cultural or social attraction.


**Figure 2: Recommendations**
Source: Own

These probabilities are dynamically adjusted based on user feedback and evolving dataset trends, ensuring that recommendations become increasingly accurate over time. By analyzing probability scores, users can prioritize activities and locations that best align with their personal interests, leading to an optimized travel experience. This is considered essential as tourist preferences are initially assessed through structured questions based on their stated interests. However, in reality, a visitor may find something they initially considered uninteresting to be highly enjoyable, or vice versa. Since tourism is dynamic and influenced by mood and external factors, incorporating feedback is essential. This allows the algorithm to adjust recommendations not only based on initial preferences but also on post-visit evaluations, ensuring a more accurate and personalized experience.

As mentioned above, in order to further support decision-making, users can access the Tourism Statistics Portal, which provides descriptive analytics on visitor trends. The platform offers insights into gender distribution among visitors, the most popular travel periods, preferred modes of travel (individual, group, or family), and the primary means of transportation used. By analyzing these factors, stakeholders and visitors alike gain a clearer understanding of tourism patterns in Serres. Although many factors were examined, we highlight a few significant patterns that highlight the system's significance and impact.

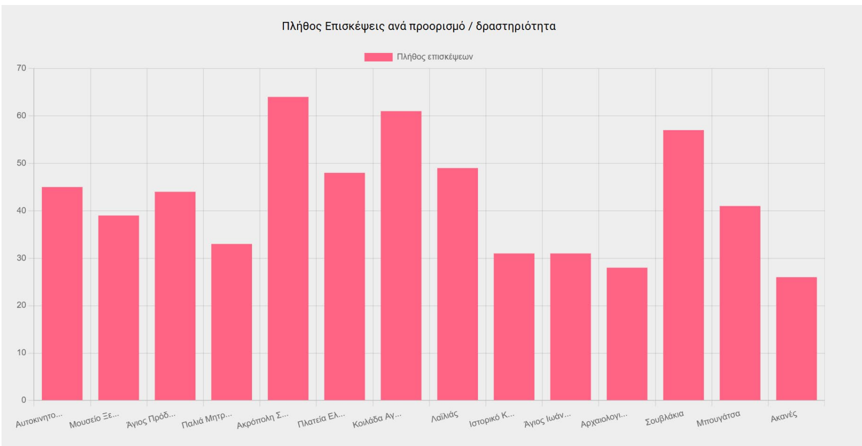


**Figure 3: Visit Frequency by destination or activity**

Source: Own

An example of such an analysis is presented in Figure 3, which illustrates the number of visits per destination or activity. This bar chart highlights locations such as Agios Prodromos, the Serres Circuit, and Lailias as some of the most popular among tourists. Furthermore, the data indicates a strong preference for local cuisine, as reflected by the high level of interest in culinary experiences like Bougatsa and Souvlaki.

The bar chart presented in Figure 4, illustrates visitor interests depending on travel style (solo travelers, family travelers, and groups of friends). It highlights how different types of travelers prioritize various experiences. A key observation is that gastronomy receives the highest level of interest across all groups, indicating its universal appeal among tourists. However, preferences for the second most preferred activity vary. Family travelers and groups of friends show a greater preference for cultural activities, making it their second-highest priority. Solo travelers, on the other hand, rank entertainment as their second choice, demonstrating a distinct preference for social and recreational experiences over cultural ones.

Finally, the bar chart in Figure 5 illustrates seasonal variations in visitor interests, segmented by autumn, winter, spring, and summer. The data suggests that gastronomy consistently attracts the highest interest across all seasons, highlighting the role of local cuisine in tourism. Interestingly, nature-related activities show increased popularity among travelers in autumn. Additionally, entertainment remains consistently high during spring, summer, and winter, indicating its broad appeal across different seasons.

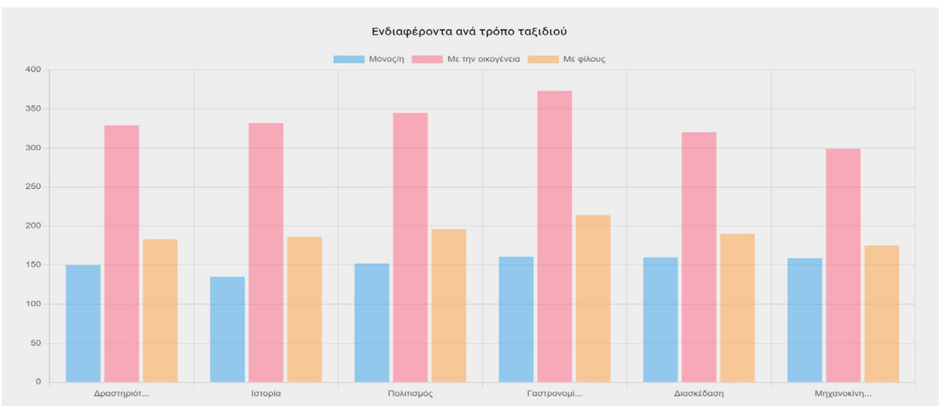


**Figure 4: Visitors interests by travel style**
Source: Own

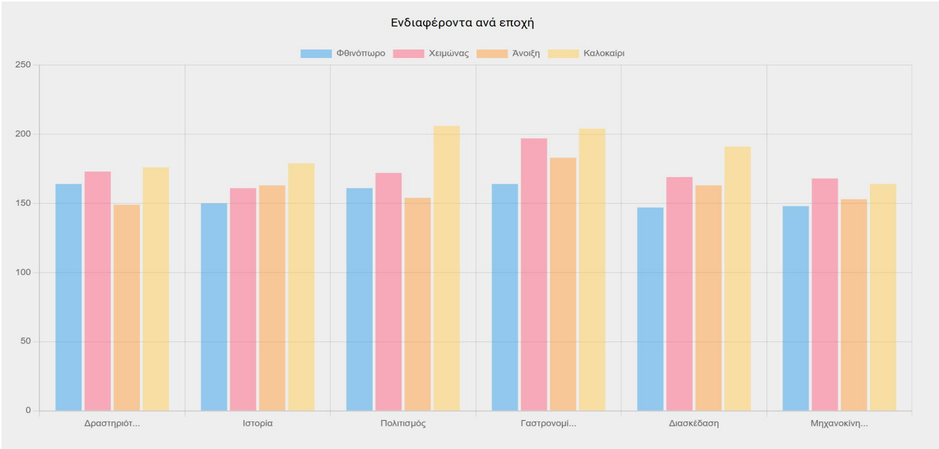


Figure 5. Seasonal interests

## 4 Conclusion

This study introduced a tourism preference prediction system that uses neural networks to generate personalized recommendations for visitors to the Municipality of Serres. Using the responses collected from visitor questionnaires, the system generates personalized recommendations by selecting five out of a total of fourteen possible destinations or activities. These recommendations are determined based on a probability score, which reflects how well each option aligns with the visitor's preferences. The predictive model ensures that the suggested destinations or activities are tailored to individual interests, enhancing the overall tourism experience while continuously improving through user feedback. To further support decision-making, users can access a portal, which provides descriptive analytics on visitor trends. The platform offers insights into gender distribution among visitors, the most popular travel periods, preferred modes of travel (individual, group, or family), and the primary means of transportation used. By analyzing these factors, stakeholders and visitors alike gain a clearer understanding of tourism patterns in Serres. Future work could focus on expanding the dataset, both in terms of sample size and questionnaire scope, while ensuring the survey remains concise and user-friendly. Additionally, increasing the number of recommendations provided, would enhance the system's ability to offer more diverse and specialized suggestions. These improvements would contribute to a more comprehensive, adaptable, and personalized tourism experience, further refining the system's ability to support data-driven decision-making in tourism management.

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