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THE IMPACT OF AN ARTIFICIAL INTELLIGENCE-BASED FORECASTING MODEL ON THE DEVELOPMENT OF SUSTAINABLE TOURISM

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Abstract: This research investigates the application of artificial intelligence (AI) and Web 3.0 technologies in promoting sustainable urban tourism, with a particular focus on demand forecasting and environmental impact assessment. The study presents a two-layered AI-based model aimed at supporting data-driven decision-making in destination management, addressing the need for forward-looking strategies that align with both operational and sustainability goals. The research applies the Facebook Prophet algorithm to forecast monthly tourism demand in two Hungarian cities—Budapest and Győr—selected for their contrasting tourism profiles. Forecast outputs were then integrated into a sustainability impact module estimating carbon dioxide emissions, water consumption, and waste generation, based on empirically defined conversion factors. Results indicated strong seasonal peaks in Budapest, with over 1.3 million overnight stays projected for August 2026, and corresponding environmental impacts surpassing 62,000 tons of CO_2. In contrast, Győr exhibited more moderate fluctuations and lower error margins, reflecting a more stable tourism pattern. Forecast accuracy was assessed using MAE, RMSE, and MAPE metrics, showing acceptable performance for strategic use, although with reduced reliability in low-demand periods. The sustainability module effectively highlighted peak periods of ecological burden, enabling targeted interventions such as infrastructure scaling, service optimization, and seasonal policy adjustments. In addition to its forecasting functionality, the model offers practical guidance for municipalities by identifying where and when ecological pressure is likely to arise. The dual-model framework offers a scalable and replicable approach for cities seeking to balance tourism growth with environmental and community well-being. By integrating predictive analytics with sustainability assessment, the model provides valuable insights into the timing and magnitude of tourism's impact. This supports smarter capacity planning, emission reduction strategies, and the alignment of visitor flows with local resilience thresholds. The findings contribute to the evolving discourse on smart and sustainable tourism in the Web 3.0 era, positioning AI as a critical enabler of holistic and proactive destination management.

Keywords: artificial intelligence, tourism demand forecasting, sustainable tourism, urban tourism, smart destination management, machine learning in tourism

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INTRODUCTION

The rapid advancement of digital technologies, including Web 3.0 and artificial intelligence (AI), is opening up new opportunities in the tourism industry on a daily basis. The decentralized platforms of Web 3.0 and AI-based applications enable more personalized and efficient services, while also contributing to the achievement of sustainability goals. For example, the application of AI significantly enhances the efficiency and sustainability of tourism in the world's leading tourist destinations. These innovations not only improve the visitor experience but also promote environmental and social sustainability. The development of tourism has a significant impact on the environment and local communities. Poorly planned and managed tourism can lead to environmental degradation, including the overconsumption of natural resources and increased waste generation (Baloch et al., 2023). Furthermore, the sociocultural structures of local communities may also be altered due to the influence of tourism, which can result in the erosion of local identity and traditions. Therefore, sustainable management of tourism is essential, one that considers both environmental and social factors (Alamineh et al., 2023).

The aim of the present research is to contribute to the sustainable development of tourism through the application of Web 3.0 and AI technologies, specifically by designing an AI-based model. The integration of intelligent automation and blockchain technology into tourism offers a means to address sustainability issues, such as minimizing food waste and reducing environmental footprints (Majid, Iis et al., 2023). Through its practical application, this research enables tourism industry stakeholders to plan and manage their activities more efficiently, while simultaneously contributing to the achievement of sustainability goals. The research has two main objectives:

1. Development of a tourism demand forecasting AI model: To create an artificial intelligence-based model capable of predicting tourism demand on a monthly basis, broken down by specific cities.

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2. Integration of a sustainability impact assessment model: To combine demand forecasts with an AI module that estimates the ecological and environmental burden of the predicted tourist traffic, including carbon dioxide emissions, water consumption, and waste generation. Within this framework, the following research questions arise: **RQ1:** To what extent is the AI-based tourism demand forecasting model capable of accurately predicting tourism demand in different cities? and **RQ2:** How can the sustainability impact assessment model be integrated into demand forecasting, and with what level of accuracy can the environmental effects of tourism be estimated?

The research is guided by the following hypotheses:

1. The AI-based demand forecasting model is capable of accurately predicting tourism demand, taking into account seasonal and regional differences.
2. Through the integration of the sustainability impact assessment model, the environmental impacts of tourism can be precisely determined, which supports more sustainable tourism management.

LITERATURE REVIEW

Digital Tourism and Web 2.0 vs. Web 3.0

The relationship between tourism and digital technologies has undergone significant transformation over the past two decades. The emergence of Web 2.0 enabled a new type of interaction between tourists and tourism service providers, while Web 3.0—characterized by the use of semantic web and decentralized systems—has brought a higher degree of personalization, security, and data interpretation to the sector. The evolution of the concept of digital tourism is closely linked to the proliferation of these web generations, and increasingly incorporates blockchain (Kupi et al., 2025), artificial intelligence (AI), and Internet of Things (IoT) technologies (Gretzel, Reino et al., 2015).

Web 2.0, often associated with the "read-write" internet, enabled tourists to actively create content, such as travel blogs, reviews, or social media posts. This user-generated content (UGC) revolutionized tourism marketing and decision-making mechanisms (Mariani & Borghi, 2019). Travelers no longer relied solely on official tourism information, but increasingly on each other's experiences, leading to decentralized trust and the dominance of reputation systems (e.g., TripAdvisor).

However, Web 2.0 did not solve structural challenges in digital tourism, such as the over-centralization of data, the lack of transparency, and the increasing digital ecological footprint (Stankov et al., 2020). These limitations laid the groundwork for the need to adopt Web 3.0, which promises decentralized, data-centric, and AI-supported operations.

Web 3.0—often referred to as the “semantic web” or “decentralized web”—is opening new horizons in tourism as well. AI-based systems are capable of analyzing tourist behavior patterns and offering personalized experiences (Del Vecchio et al., 2018). Furthermore, blockchain technology enables the use of smart contracts for travel bookings, ensuring transparency and security (Mariani et al., 2018). This new phase of digital tourism—often called “smart tourism”—integrates IoT devices, Big Data analytics, and predictive modeling, allowing cities and destinations to proactively manage travel demand and sustainability considerations (Gretzel, Werthner et al., 2015). One of the most important contributions of Web 3.0 is not only the enhancement of the tourist experience, but also the improved planning of local communities, environments, and infrastructure. It is important to note, however, that the application of Web 3.0 in tourism is still in its early stages and faces significant challenges - especially due to lack of technological literacy, regulatory uncertainty, and issues of interoperability (Yung & Khoo-Lattimore, 2019). The development of digital competencies and the spread of open-source platforms may play a key role in democratizing the technology. Thus, while Web 2.0 laid the foundations of digital tourism through community interaction, Web 3.0 offers a more intelligent, personalized, and structured approach. Future research and practice should focus on integration, social impacts, and maximizing sustainability potential.

The Role of Artificial Intelligence in Tourism

The rise of artificial intelligence (AI) in recent years has had a significant impact on the tourism sector, transforming the way services are provided and opening new possibilities for achieving sustainability goals. The use of AI in tourism not only serves to increase efficiency but also contributes to the realization of Sustainable Development Goals (SDGs) (Gössling & Mei, 2025). One of the most important applications of AI in tourism is demand forecasting. The latest transformer-based models enable more accurate forecasting of tourism demand by accounting for seasonal and trend-based variations (Li et al., 2024). These advanced algorithms are capable of processing and analyzing large volumes of data, which is essential for understanding the dynamically changing tourism markets and ensuring proper capacity planning.

In the field of virtual tourism, AI-based applications offer tourists the opportunity to experience interactive and personalized journeys without being physically present at the location. A recent study pointed out that AI-supported virtual tourism has a positive impact on tourists’ environmentally conscious behavior, encouraging the adoption of more sustainable travel habits (Wu & Wang, 2025). However, the application of AI in tourism is not without challenges. Achieving sustainability goals requires a thorough assessment of the risks and opportunities generated by AI. Gössling and Mei (2025) emphasize that although AI can contribute to the sustainability of tourism, potential negative impacts—such as social tensions resulting from job automation or data privacy concerns—must also be considered.

Moreover, the role of AI and intelligent automation in sustainable tourism is becoming increasingly prominent. A comprehensive literature review highlighted that the application of intelligent automation offers numerous opportunities to address the challenges of sustainable tourism, including more efficient use of resources and reduction of environmental impacts (Majid, Tussyadiah, et al., 2023). Thus, artificial intelligence plays a significant role in transforming tourism, particularly in achieving sustainability goals. However, the responsible and thoughtful application of this technology is essential, with careful consideration of both its opportunities and potential risks.

Sustainability in the Tourism Context

The concept of sustainability has gained increasing importance in tourism in recent years, as the growth of global tourism has raised numerous environmental, social, and economic challenges. The aim of sustainable tourism is to meet the needs of present tourists and host regions while protecting and enhancing the potential for the future (Guo et al., 2019). This includes the preservation of natural and cultural resources, supporting the well-being of local communities, and ensuring a fair distribution of economic benefits. In recent years, the significance of sustainable tourism has further increased due to the impact of the COVID-19 pandemic. The pandemic highlighted the vulnerability of the tourism sector and made it necessary to develop more sustainable and resilient tourism practices. According to research, the development of sustainable tourism can contribute to the revitalization of the tourism industry by helping reduce mass tourism and promoting safer travel experiences (Higgins-Desbiolles, 2020). The implementation of sustainable tourism comes with several challenges. The involvement and support of local communities are crucial to the success of sustainable tourism. Studies have pointed out that participation and commitment of local residents are essential for sustainable development in community-based ecotourism (Radwan et al., 2023). Moreover, the environmental impacts of tourism development must also be considered, as poor planning and management can have negative effects on the natural environment (Buckley, 2001). Education and awareness-raising also play a vital role in promoting sustainable tourism. Increasing environmental awareness among tourism workers and tourists alike can contribute to the spread of more sustainable practices and to the reduction of environmental burdens (Rosiński, 2023).

The Impact of Tourism on the Well-Being of Local Communities

Tourism has a significant impact on the social, economic, and environmental aspects of host communities around the world. While tourism can contribute to economic growth and the preservation of cultural heritage, it is also important to consider its potential negative consequences for the well-being of local populations. One such aspect is the role of economic effects. Tourism development can create jobs and increase local revenues, contributing to the economic well-being of communities. However, the economic benefits derived from tourism are not always distributed evenly, which can lead to social inequalities. For example, some studies suggest that tourism-generated revenues often go to larger enterprises, while smaller local businesses benefit less from these advantages (Markandya et al., 2008).

Beyond economic dimensions, tourism can support the preservation of cultural heritage and strengthen local identity. Nevertheless, excessive tourism may lead to cultural homogenization and distortion of local customs, which can negatively affect community well-being. Moreover, interactions between tourists and residents may create tensions, especially when tourist behavior does not align with local norms (Gössling, 2001). Tourism growth can also place a burden on the environment, which directly affects the quality of life for local residents. Excessive visitor numbers may lead to the depletion of natural resources, pollution, and habitat destruction. Therefore, environmental impacts must be considered in the development of sustainable tourism, with a strong focus on minimizing those effects (Becken, 2014).

The active involvement of local communities in tourism planning and management is crucial for sustainable development and community well-being. Resident participation increases support for tourism and contributes to positive social outcomes. For example, community-led tourism projects can boost residents' income and strengthen social cohesion (Drumm & Moore, 2005). Educational programs and training related to tourism help improve the skills of local people, increasing their employability and contributing to the economic development of the community. Through education, local residents gain a better understanding of the benefits and challenges of tourism, which promotes the adoption of more sustainable tourism practices (Mir et al., 2024). In conclusion, tourism has a significant impact on the well-being of local communities, both positive and negative. The development of sustainable tourism requires the involvement of local residents, the equitable distribution of economic benefits, and the preservation of environmental and cultural values, while also considering all these factors in destination management and planning processes.

Web 3.0 and Artificial Intelligence in the Service of Community Well-Being

The application of AI and machine learning in tourism enables more accurate forecasting of visitor numbers and demand. For example, one study demonstrates that deep learning methods, such as convolutional neural networks, can be effectively applied to predict tourism demand, thereby improving planning and resource allocation decisions (Law et al., 2019). Another study examines the application of transformer-based models in tourism demand forecasting, highlighting their accuracy and efficiency (Zhang et al., 2025). Artificial intelligence is increasingly used not only to forecast demand but also to estimate the environmental and social impacts generated by tourism. For instance, Roumiani et al. (2023) modelled the ecological footprint of tourism in Indian national parks using AI-based simulation and pointed out how carbon dioxide emissions generated by tourists correlate with seasonal variations in visitor numbers (Roumiani et al., 2023). Similarly, Zhen (2025) developed a sustainability index combined with machine learning, which estimates the environmental burden of destinations based on variables such as water consumption, waste generation, and transportation data (Zhen, 2025). Web 3.0-based technologies—such as blockchain, smart contracts, and decentralized applications (DApps)—enable communities participating in tourism to become actively involved in processes. Several studies (e.g., Wenhua et al., 2023) emphasize that blockchain can be used to create transparent and traceable tourism ecosystems, which help ensure a more equitable distribution of revenues and enhance the competitiveness of local service providers (Wenhua et al., 2023). In addition, semantic web-based systems enable personalized information delivery and promote sustainable tourist behavior (Buhalis & Amaranggana, 2015.). This can manifest, for example, in real-time notifications about environmental pressure or in recommending less frequently visited sites.

MATERIALS AND METHODS

In the course of this research, an artificial intelligence-based multivariate tourism demand forecasting model was developed with the aim of predicting tourist traffic at a regional level, applicable both in urban and regional contexts. The study follows a quantitative, deductive approach to model development, directly linking demand forecasting based on secondary data with impact elements that are key from a sustainability perspective. The model comprises two interrelated modules:

1. Tourism demand forecasting AI model, which models the number of overnight stays using a time series–based method, broken down by month, utilizing the open-source Prophet time series forecasting algorithm.
2. Sustainability impact assessment AI module, which estimates the environmental impacts of tourism—specifically carbon dioxide emissions, water consumption, and waste generation—based on the forecasted number of overnight stays derived from the demand model.

The primary objective of this research is to develop the model itself as a practical tool for decision-makers; however, this publication presents results focusing on two Hungarian cities: Budapest and Győr. The selection of these cities was strategic, as they possess distinctly different tourism profiles: Budapest is a major destination with high volumes of international tourism, whereas Győr operates with a smaller-scale, primarily domestic visitor base.

The timeframe analyzed spans from January 2015 to December 2023, with monthly data granularity—providing sufficient input for training a reliable time series model. The analyzed data were obtained from secondary sources:

- Hungarian Central Statistical Office (KSH): monthly datasets on overnight stays, disaggregated by city;
- Google Trends: regional and time-series-based interest data specifically related to tourism searches (e.g., “Budapest hotel”, “Győr szállás”). Google Trends indices were used as additional predictors in the model;
- Empirically estimated conversion factors for the sustainability model: 1 overnight stay = 6 kg CO_2, 150 liters of water, 2 kg of waste (based on findings by Majid et al., 2023).

The analytical process began with the implementation of the Prophet model—an additive time series model that performs forecasting by accounting for trends, seasonality, and potential outliers. The model was trained separately for Budapest and Győr. This was followed by forecast validation, for which the accuracy of the model was evaluated using the MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error) indicators.

The sustainability impact estimation was then carried out by applying multiplier values to the forecasted number of overnight stays, thereby producing estimates of CO_2 emissions, water consumption, and waste generation.

Despite the model’s utility, several limitations must be acknowledged:

- Data on overnight stays may be incomplete or distorted during certain periods (e.g., during the COVID-19 pandemic);
- Sustainability multipliers are based on a single research source;
- The model does not account for local political changes, major events, or extreme weather conditions.

Future research aims to expand the models to additional cities, integrate more predictors (e.g., exchange rates, weather conditions, economic indicators), and develop interactive dashboards for use by decision-makers.

The model prototype was developed in a Python environment (Google Colab), as shown in Figure 1, enabling further expansion with additional modules—such as the sustainability impact assessment module.

```
IMPORT PANDAS AS PD
FROM PROPHET IMPORT PROPHET
IMPORT MATPLOTLIB.PYPLOT AS PLT

DF = PD.READ_CSV("BUDAPEST_GYOR_VENDEGEJSZAKAK.CSV")  # <- EZT KELL ELŐBB ELMENTENED

DF_BUDAPEST = DF[["DÁTUM", "BUDAPEST_VENDÉGEJSZAKÁK"]].RENAME(
    COLUMNS={"DÁTUM": "DS", "BUDAPEST_VENDÉGEJSZAKÁK": "Y"}
)
DF_BUDAPEST["DS"] = PD.TO_DATETIME(DF_BUDAPEST["DS"])

MODEL = PROPHET()
MODEL.FIT(DF_BUDAPEST)

FUTURE = MODEL.MAKE_FUTURE_DATAFRAME(PERIODS=12, FREQ='M')

FORECAST = MODEL.PREDICT(FUTURE)

FIG1 = MODEL.PLOT(FORECAST)
PLT.TITLE("BUDAPEST – VENDÉGÉJSZAKÁK ELŐREJELZÉSE (PROPHET)")
PLT.XLABEL("DÁTUM")
PLT.YLABEL("VENDÉGÉJSZAKÁK SZÁMA")
PLT.GRID(TRUE)
PLT.TIGHT_LAYOUT()
PLT.SHOW()

FIG2 = MODEL.PLOT_COMPONENTS(FORECAST)
PLT.TIGHT_LAYOUT()
PLT.SHOW()

DF_GYOR = DF[["DÁTUM", "GYOR_VENDÉGEJSZAKÁK"]].RENAME(
    COLUMNS={"DÁTUM": "DS", "GYOR_VENDÉGEJSZAKÁK": "Y"}
)
DF_GYOR["DS"] = PD.TO_DATETIME(DF_GYOR["DS"])


MODEL_GYOR = PROPHET()
MODEL_GYOR.FIT(DF_GYOR)
FUTURE_GYOR = MODEL_GYOR.MAKE_FUTURE_DATAFRAME(PERIODS=12, FREQ='M')
FORECAST_GYOR = MODEL_GYOR.PREDICT(FUTURE_GYOR)

FIG1 = MODEL_GYOR.PLOT(FORECAST_GYOR)
PLT.TITLE("GYŐR - VENDÉGÉJSZAKÁK ELŐREJELZÉSE (PROPHET)")
PLT.XLABEL("DÁTUM")
PLT.YLABEL("VENDÉGÉJSZAKÁK SZÁMA")
PLT.GRID(TRUE)
PLT.TIGHT_LAYOUT()
PLT.SHOW()

FIG2 = MODEL_GYOR.PLOT_COMPONENTS(FORECAST_GYOR)
PLT.TIGHT_LAYOUT()
PLT.SHOW()

FROM SKLEARN.METRICS IMPORT MEAN_ABSOLUTE_ERROR, MEAN_SQUARED_ERROR, MEAN_ABSOLUTE_PERCENTAGE_ERROR
IMPORT NUMPY AS NP

MAE = MEAN_ABSOLUTE_ERROR(MERGED_BUDAPEST["Y"], MERGED_BUDAPEST["YHAT"])
MSE = MEAN_SQUARED_ERROR(MERGED_BUDAPEST["Y"], MERGED_BUDAPEST["YHAT"])
RMSE = NP.SQRT(MSE)
MAPE = MEAN_ABSOLUTE_PERCENTAGE_ERROR(MERGED_BUDAPEST["Y"], MERGED_BUDAPEST["YHAT"])

PRINT("MAE:", ROUND(MAE, 2))
PRINT("RMSE:", ROUND(RMSE, 2))
PRINT("MAPE:", ROUND(MAPE * 100, 2), "%")


DF_BUDAPEST["MONTH"] = DF_BUDAPEST["DS"].DT.MONTH
SEASONALITY = DF_BUDAPEST.GROUPBY("MONTH")["Y"].MEAN()
PRINT(SEASONALITY)
PRINT(DF_BUDAPEST.GROUPBY("MONTH")["Y"].MEAN())


FORECAST_2026 = FORECAST[FORECAST["DS"].DT.YEAR == 2026]
FORECAST_2026[["DS", "YHAT"]]
FORECAST[FORECAST["DS"].DT.YEAR == 2026][["DS", "YHAT"]]
```

Figure 1. Prototype of the Model, own source

RESULTS

The results of this study are based on the output of two artificial intelligence–based models: one designed to forecast tourism demand, and the other to estimate sustainability-related impacts. For training the Prophet model, monthly overnight stay data from 2015 to 2023 were used. In the case of Budapest, the average number of overnight stays exceeded 1 million per month during the summer, while in Győr, the monthly figures hovered around 50,000. The model generated forecasts from 2024 through 2026, which were analyzed both visually and using statistical metrics. Forecasting accuracy for Budapest:

• MAE (Mean Absolute Error): 219.82
• RMSE (Root Mean Squared Error): 267.80
• MAPE (Mean Absolute Percentage Error): 43.1%

The relatively high MAPE value highlighted the model's weakness in forecasting for the lower-volume months (January and February)—although values between 20% and 50% are generally considered acceptable. In contrast, the summer season forecasts proved to be much more accurate. The Prophet model reliably captured the annual seasonality cycles and exhibited a stable, gradually increasing long-term trend.

As shown in Figure 2, the highest forecasted value is projected for August 2026, with over 1.3 million overnight stays.

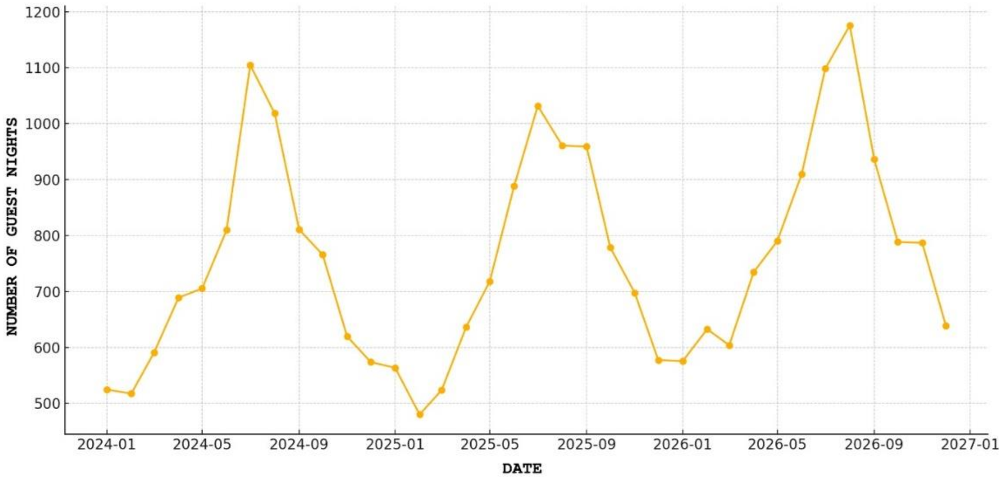

Figure 2. Number of Actual and Forecasted Overnight Stays (Budapest) (Source: own analysis output, based on the Prophet forecast)

Despite the smaller sample size, the error metrics of the Győr model were more favorable:

• MAE: 6.42
• RMSE: 9.17
• MAPE: 35.8%

This is due to the fact that - as illustrated in Figure 3 - Győr exhibited smaller annual fluctuations, fewer outliers, and a more even trend. The model reliably detected the summer peak periods here as well, although the annual trend did not show a significant upward trajectory.

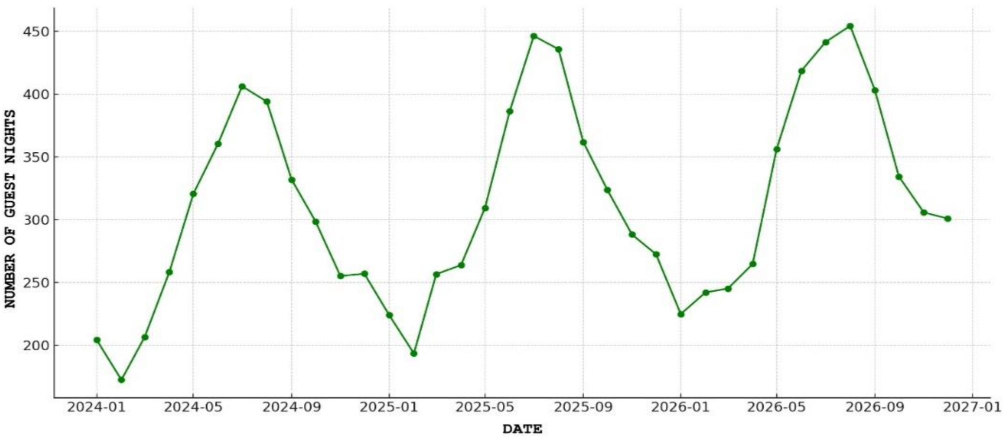

Figure 3. Number of Actual and Forecasted Overnight Stays (Győr) (Source: own analysis output, based on the Prophet forecast)

Using the forecasted number of overnight stays, the sustainability impact assessment module generated the following indicators: Budapest (2026):

• Estimated number of overnight stays: approx. 10.4 million
• CO_2 emissions: ~62.4 million kg (62,400 tons)
• Water consumption: ~1.56 billion liters
• Waste generation: ~20.8 million kg (20,800 tons)

Győr (2026):
• Estimated number of overnight stays: approx. 790,000
• CO_2 emissions: ~4.74 million kg
• Water consumption: ~118.5 million liters
• Waste generation: ~1.58 million kg

According to the data, Budapest's sustainability burden is more than ten times greater than that of Győr (see Figure 4), which is consistent with the difference in overnight stay volumes. In the annual breakdown charts, the highest emission and consumption values were recorded during the peak summer season months. The three subcharts in Figure 4 illustrate the predicted environmental impact of tourism in Győr for the period 2024–2026.

- **(a)** The CO_2 emissions chart shows seasonal peaks in emissions during the summer months, in correlation with higher visitor traffic.
- **(b)** Water consumption follows a similar pattern, reflecting increased infrastructure use during high season.
- **(c)** Waste generation demonstrates a steady rise across the summers, with lower values during the winter months.

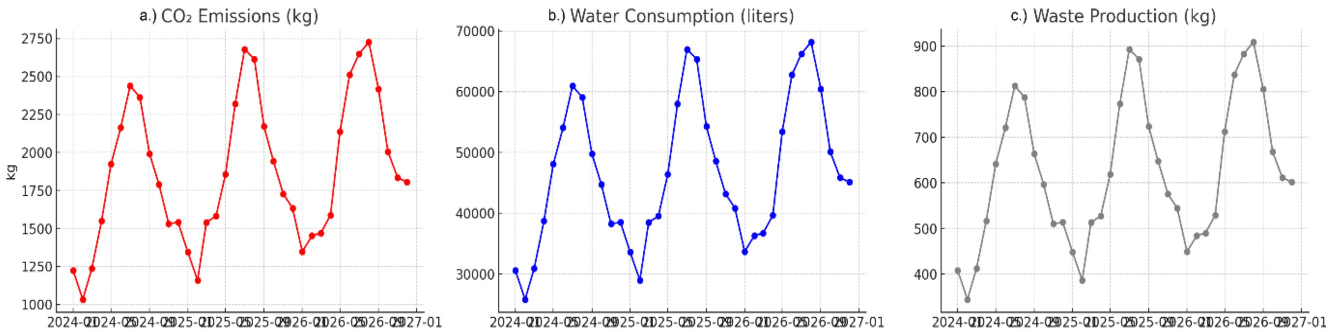

Figure 4. Sustainability Impact Forecast - Győr, 2024 – 2025 (Source: own analysis output, based on the Prophet forecast)

The results and impacts of the models for the two cities differ significantly. In terms of volume, Budapest's tourism sector is at least ten times larger than that of Győr. When analyzing seasonality, the summer peak months have an extreme impact in Budapest, whereas in Győr, the fluctuations are more moderate. The model errors are lower in the case of Győr, but the practical significance of the results is greater for Budapest. The CO_2 emissions, water consumption, and waste generation indicators increase proportionally with the volume of overnight stays.

While the model results were applied specifically to these two Hungarian cities, the framework can be extended to multiple areas, such as destination management, where traffic forecasts support seasonal capacity planning, as well as accommodation and workforce allocation. In the formulation of environmental strategies, the sustainability module's indicators aid in developing plans to reduce CO_2 footprints and water consumption. In the context of risk management, the early detection of seasonal surges and declines enables timely intervention.

The findings from this two-stage artificial intelligence–based model demonstrate that, even when relying solely on secondary (or potentially primary) data, it is possible to produce accurate demand forecasts and environmental impact estimates that meaningfully support sustainable destination management and the improvement of local community well-being.

DISCUSSION

The tourism demand forecasts revealed strong seasonality in both Budapest and Győr, although the magnitude of variation differed significantly. In Budapest, the number of overnight stays increases by approximately 1.5 times during the summer peak months compared to the winter period. This indicates that tourism in Budapest is highly seasonal, concentrated mainly in the summer, which poses considerable challenges for sustainability. Imbalances in seasonality may lead to infrastructure overload, hinder stable workforce management, and complicate the maintenance of consistent service quality. In contrast, Győr displayed a much more balanced and less volatile demand, creating a more favorable context for sustainable destination management. In such destinations, the temporary overuse of infrastructure is less prominent, making environmental pressures more predictable and manageable.

By using the forecasted number of overnight stays, the sustainability indicators generated by the model—along with their seasonal distribution—allowed the study to identify when the greatest ecological burdens occur. During the summer months, CO_2 emissions, water consumption, and waste generation increase dramatically. This highlights that the environmental impacts of tourism are not linear but rather concentrated in specific time periods.

Furthermore, the model enabled the spatial and temporal analysis of impacts, rather than limiting evaluation to absolute figures. This provides a data-driven foundation for decision-making processes, allowing authorities to determine when and where specific interventions are required to improve sustainability indicators.

The ecological pressure caused by tourist flows manifests not only in environmental terms but also affects the daily quality of life of local communities. Excessive tourism during peak periods can lead to increased noise levels, air pollution, traffic congestion, and deterioration of public services available to residents (e.g., hygiene, cleanliness, parking availability). These effects diminish well-being, heighten frustration, and may ultimately reduce local tolerance for tourism.

In contrast, Győr's more balanced tourism demand minimizes such negative impacts. A lower, but more stable tourism volume tends to have a direct and positive effect on local communities: it can contribute to the development of public services, the growth of local businesses, and enhance community cohesion.

The AI-based model presented in this study enables destinations and municipalities to plan their tourism capacity consciously and based on data. With the help of accurate forecasts, infrastructure overload can be prevented, and the timing of public service development can be optimized. The sustainability module further enables the setting and tracking of emission-reduction goals. This is particularly important in the era of Web 3.0, where tourism must be viewed not merely as an engine of economic growth but also as a balancing element for maintaining local well-being and ecosystem equilibrium.

Throughout the study, several research questions were addressed. The first of these was:

(RQ1) *To what extent can an AI-based demand forecasting model accurately predict tourism demand in different cities?*

This question was linked to the following hypothesis:

(H1) *The AI-based demand forecasting model can predict tourism demand with high accuracy, taking into account seasonal and regional differences.*

The Prophet-based demand forecasting model was tested using data from two cities with distinct tourism profiles—Budapest and Győr. The model predicted the number of overnight stays on a monthly basis, incorporating both seasonal patterns and historical time series.

In the case of Budapest, the model exhibited higher absolute error, which is to be expected given the city's high-volume and volatile tourism sector. Nevertheless, the MAE (219.82), RMSE (267.8), and a relatively high MAPE (43.1%) do not necessarily indicate poor performance. The model was able to identify seasonal peaks and troughs, and its trend component effectively captured the post-COVID recovery trajectory.

In contrast, Győr, with its smaller volume and less turbulent tourism dynamics, yielded more stable predictions with lower error values, albeit with less pronounced seasonality.

While the model may not achieve equal accuracy across all periods or cities, it is suitable for forecasting major tourism trends, spikes, and seasonal variations. These forecasts provide valuable input for sustainable destination management, including capacity planning, marketing timing, and infrastructure forecasting.

The second research question posed was:

(RQ2) *How can the sustainability impact assessment model be integrated into demand forecasts, and with what accuracy can tourism's environmental impacts be estimated?*

This was accompanied by the second hypothesis:

(H2) *By integrating the sustainability impact assessment model, it is possible to accurately estimate the environmental pressures generated by tourism, thereby supporting more sustainable tourism management.*

The sustainability impact assessment module was built on the outputs of the demand forecasting model. It calculated environmental burdens based on monthly overnight stays, using the following conversion factors:

• 6 kg CO_2 per tourist per night
• 150 litres of water per tourist per night
• 2 kg of waste per tourist per night.

These values were directly derived from the AI model's forecasts, enabling the calculation of monthly and annual environmental impacts in advance.

The results clearly identified peak burden periods (especially in the summer), when CO_2 emissions and water consumption increased significantly, particularly in Budapest. For instance, during a single summer month, hundreds of thousands of kilograms of CO_2 and millions of liters of water may be consumed, unless active capacity management or sustainable tourism incentives are applied.

Such foresight is invaluable not only for destination management, but also for infrastructure planning and community development. The ability to forecast when and where environmental burdens will be most intense allows for optimized resource management, including urban service provision (e.g., water systems, waste management, public transport) and the development of sustainability indicators.

In conclusion, the responses to both research questions and the testing of the related hypotheses confirm that the two-layered AI-based system (demand forecasting and impact assessment) provides a functioning framework that can deliver useful insights even when relying solely on publicly available data. The system is scalable to other cities and regions, and can be further enhanced with additional predictors (e.g., weather data, event calendars, transportation metrics).

This dual-model approach is valuable not only because of its predictive accuracy, but also because it promotes community well-being, smarter resource use, and the long-term sustainability of tourism.

CONCLUSIONS

The aim of this study was to explore how artificial intelligence (AI) can be applied to forecast tourism demand and how such predictions can be used to develop a sustainability impact assessment model that supports community well-being and informed tourism management. The research findings confirmed that even a two-tier AI model based on publicly available data is capable of identifying demand trends and quantifying related environmental impacts.

The demand forecasting model, built using the Prophet algorithm, effectively identified seasonality, trend shifts, and volume differences in both Budapest and Győr. The accuracy of the forecasts was evaluated using the MAPE, MAE, and RMSE indicators. As expected, errors were higher in Budapest due to the larger volume and fluctuation of tourism, whereas Győr produced more precise results due to its smaller and more stable tourism patterns.

The sustainability impact assessment model successfully estimated CO_2 emissions, water consumption, and waste generation based on overnight stays. The highest ecological burdens were recorded in the peak summer months, underscoring the necessity of strategies aimed at balancing seasonality. The model offers a practical tool for decision-making, enabling early identification of peak periods and their environmental consequences, thus facilitating long-term planning. Based on the research findings, several recommendations can be made:

- Stimulate off-season tourism with targeted promotional campaigns aimed at attracting specific market segments, thereby reducing seasonality.
- Scale up infrastructure during peak months (e.g., waste collection, water supply systems).
- Implement awareness campaigns to minimize environmental damage during high-traffic periods.
- Develop an interactive dashboard version of the model to support municipalities and accommodation providers with capacity management.
- Integrate sustainability indicators into tourism planning KPIs to support data-driven policy.

Future objectives of the research include extending the model to additional cities and tourism regions, as well as integrating supplementary predictor variables (e.g., weather data, event calendars, exchange rates), which would further enhance the model's predictive capabilities. The study also aims to explore the role of Web 3.0 technologies in tourism—such as blockchain, tokenization, and NFT-based access solutions. AI-based modelling opens up new opportunities to guide tourism not only from an economic but also from a social and environmental perspective. The toolset presented in this paper may contribute to the evolution of tourism in the Web 3.0 era into a more sustainable, inclusive, and data-driven industry that serves not only visitors but also the well-being of local communities.

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