Palmira Papsiene

The Influence of Dynamic Factors in the Management of the Load on Tourist Infrastructure Through the Organizational Reflex

Abstract

The influence of dynamic factors on the management of congestion in tourist infrastructure is widely studied in academic literature. The tourism sector is one of the most important economic engines in many countries, contributing to job creation, income generation, and cultural exchange. However, managing the load on tourist infrastructure is complex and requires accounting for dynamic factors such as seasonal fluctuations, changes in event intensity, and unexpected environmental or economic disruptions. This article analyzes how seasonality and events affect the load on tourist infrastructure and offers recommendations for managing these dynamic factors effectively. Traditional deterministic models often cannot accurately predict these situations because of high uncertainty and limited information. This study proposes a structured fuzzy decision-making model that allows for flexible assessment of both quantitative and qualitative indicators characterizing the load on tourism infrastructure. Fuzzy logic enables work with uncertain data, and the concept of organizational reflex allows quick adaptation to changing conditions through optimized management decisions. Theoretical modeling techniques revealed connections, and computer simulation examined these connections under different conditions using Spyder (a Python environment based on NumPy, etc.), which provides the necessary functions to perform calculations and visualize results.

Keywords: tourist infrastructure, dynamic factors, organizational reflex

1. Introduction

Tourism infrastructure management is a critical area that requires dynamic, adaptive solutions to optimally distribute visitor flows and prevent infrastructure congestion. Traditional management models, such as carrying capacity theory (Mathieson & Wall, 1982) and the tourism life cycle (Butler, 1980), remain widely used, yet modern research shows that these methods often fail to adequately account for the influence of dynamic factors.

Dynamic factors include seasonal fluctuations, events, transport accessibility, and economic and climate change, which shape infrastructure loads and the sustainability of tourist areas (Sæþórsdóttir et al., 2019). For example, seasonality significantly affects the sustainability and capacity of tourist destinations – these areas often experience large fluctuations in visitor flows, leading to infrastructure congestion (Butler, 2001). Events such as festivals, concerts, or sports competitions also significantly affect tourist distribution and often cause short-term spikes in infrastructure load (Pappa et al., 2022; Drakakis et al., 2021).

Modern research emphasizes that fuzzy logic, artificial intelligence (AI), and real-time data analysis can significantly improve infrastructure load management (Xu et al., 2023; Nilashi et al., 2022). These technologies enable accurate prediction of tourist flows, optimize transportation systems, and offer flexible management strategies that help avoid congestion and improve the visitor experience.

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TOURISM
An International Interdisciplinary Journal
Original Research Article
Vol. 74/ No. 4/ 2026/ 609 - 626
UDC: 338.48:005.71; https://10.37741/t.74.4.5
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Vaitkevicius et al. (2021) propose a model for how an organization's human resources respond to signals from the global environment. In this context, one advanced management methodology is applying the organizational reflex principle, which enables real-time analysis of infrastructure load and automatic adaptation of solutions. This model relies on an adaptive regulatory mechanism that activates when infrastructure load exceeds a certain threshold. For example, if the number of tourists in a given area reaches a critical threshold, control mechanisms such as redirecting visitor flows to alternative areas, a reservation system, or temporary restrictions may be activated.

GIS systems have also become an important tool for infrastructure management. Research shows that Geographic Information Systems (GIS), when combined with artificial intelligence techniques, can improve understanding of tourist distribution and enhance infrastructure planning (Boers & Cottrell, 2007). For example, some European tourist areas already have smart transport and visitor monitoring systems in place to help dynamically regulate tourist flows and improve urban governance (Bertocchi et al., 2020; Pappa et al., 2022).

Infrastructure congestion management is closely linked to sustainability strategies. Recent research suggests that efficient infrastructure management can improve an area's competitiveness and reduce negative environmental impacts (Cucculelli & Goffi, 2016; Apriyanti, 2024). In addition, in the context of the pandemic, dynamic models have been shown to help better respond to sudden changes in tourist flows (Thalmeiner et al., 2021; Ullah et al., 2016). However, tourist flows can overload tourism infrastructure, which hinders the development of an effective decision-making mechanism.

The goal is to create and apply a structured fuzzy model that, based on organizational reflexes, would optimize the load on tourism infrastructure by adjusting dynamic factors.

In summary, integrating organizational reflex and fuzzy logic methods with real-time data analysis systems enables more efficient management of tourist flows and helps address infrastructure congestion. These solutions not only improve the tourist experience but also ensure the long-term sustainability of tourist areas.

2. Literature review

2.1. Tourism infrastructure management

Tourism infrastructure management is a critical area focused on allocating and using available resources effectively to meet tourists' needs. In developing the discussion on infrastructure congestion management in tourism, it is necessary to rely on key theoretical models, including visitor flow analysis (Butler, 1980), life cycle theory for tourist facilities, and the concept of carrying capacity, which defines infrastructure limits (Mathieson & Wall, 1982). Simón et al. (2004) examine alternatives to the carrying capacity concept for this model and propose solutions to identify, manage, control, and enhance the environmental capacity of a tourist site. For example, a tourist-flow monitoring system in Venice helps optimize visitor numbers (Bertocchi et al., 2020), and in Japan, some popular facilities require pre-reservations to reduce infrastructure load (Mortazavi & Cialani, 2017). The literature emphasizes that infrastructure congestion management depends on factors such as visitor flow intensity, infrastructure adaptability, and management strategies (Hall, 2008; Page, 2019). Gonzalez et al. (2008) examine patterns of human mobility that are critical to understanding visitor traffic intensity and its impact on infrastructure. Bramwell and Lane (2011) highlight the importance of management and strategies in addressing tourism congestion and sustainability. Ritchie and Crouch (2003) discuss the competitive nature of travel and the importance of managing visitor flows to maintain sustainability, while Cucculelli and Goffi (2016) affirm the role of sustainability as an essential factor in the competitiveness of a tourist destination. Apriyanti (2024) focuses on the importance of tourism infrastructure accessibility in increasing tourist attendance in domestic and international tourism, and Dredge et al. (2016)

discuss various planning and policy frameworks that can be used to effectively manage tourism congestion. Boers and Cottrell (2007) present a conceptual, geography information systems (GIS)-supported sustainable tourism infrastructure planning (STIP) framework that includes attractions, services, and transportation facilities. In recent years, research on tourism infrastructure management has increasingly emphasized the application of artificial intelligence technologies. Artificial intelligence travel applications are becoming a new tool for managing information flow and consumer behavior, enabling more effective forecasting of tourist flows, optimization of infrastructure load, and personalization of services (Skandali & Tsourvakas, 2025).

In summary, addressing tourism congestion and ensuring sustainability requires considering visitor flow intensity and management strategies. Efficiently managing infrastructure loads and planning sustainable tourism infrastructure should also account for traction, services, and transport.

2.2. The concept of dynamic factors

Dynamic factors can serve as both risk factors and sources of opportunities, changing the structure and intensity of tourist flows.

Dynamic factors are changing factors that affect tourist flows and infrastructure congestion. Prideaux (2005) examines the structure of bilateral tourism and identifies five broad categories of factors that may affect the overall size of tourism flows: private sector factors, intangible factors, economic factors, and external political and health factors.

The dynamic factors that influence tourist flows and infrastructure congestion are crucial to understanding the complexity of tourism management. These factors can vary widely, affecting how travel destinations will cope with the influx of visitors and the strain on infrastructure. The literature identifies several key dynamic factors, including visitor flow intensity, infrastructure adaptation, and management strategies, which are essential for effective congestion management in the context of tourism.

2.2.1. Visitor flow intensity

Research provides a solid foundation for understanding visitor flow intensity in tourism management, including the factors that determine it, its impact on infrastructure and sustainability, and effective management strategies to address visitor flow intensity-related problems in tourism.

Visitor flow intensity is an essential concept in tourism management, referring to the number and distribution of tourists at a destination over time. Understanding visitor traffic intensity is essential for efficient planning and management of tourist attractions, as it directly affects infrastructure, the visitor experience, and the destination's sustainability. González et al. (2008) examine patterns of human mobility, offering insights into how individual behavior shapes overall visitor traffic intensity in urban environments. Bramwell and Lane (2011) discuss tourism management and how visitor flow intensity affects sustainability efforts in popular destinations. They examine the factors influencing global tourist flows and how these factors relate to visitor flow intensity in different destinations. Shymanskyi et al. (2022) examine the factors influencing global tourist flows and how these factors relate to visitor flow intensity in various locations.

Visitor flow intensity refers to the number and distribution of tourists at a destination over a given period. High visitor flow can cause congestion, especially at popular attractions. Studies show that several factors influence tourist flow intensity, including the availability of communication infrastructure, seasonal changes, and special events. Salinas Fernández et al. (2020) highlight that key resources such as natural objects and cultural heritage significantly affect destination competitiveness and, consequently, the intensity of visitor flows. Yin et al. (2019) discuss how transportation development, e.g., high-speed rail, can change tourism's spatial structure and affect the intensity of visitor flows between metropolitan areas.

2.2.2. Infrastructure adaptability

Infrastructure adaptation is another key factor in managing tourist flows, especially as visitor patterns and needs change. This refers to the ability of destination infrastructure to accommodate varying levels of tourist activity without compromising visitor experience quality or environmental integrity. Therefore, amusement park experiences are significantly influenced by how well infrastructure adapts to peak visitor numbers. According to Smith et al. (2014), understanding visitor segmentation is critical to identifying appropriate management practices, including providing appropriate infrastructure. By recognizing the different needs of visitor groups, park managers can adapt infrastructure to improve the overall experience and ensure facilities meet different visitor groups' expectations. This adaptation can increase visitor satisfaction and loyalty. Chau, T. M. (2023) studied the relationship between the natural and historical/cultural environments, infrastructure, tourism security, and tourist satisfaction for travel purposes. Research results show a strong link between natural and historical/cultural environments and satisfaction with tourist attractions. The correlation coefficient between the infrastructure factor and satisfaction with tourist destinations is medium, while the coefficient for tourism safety is low. Improving tourism infrastructure is essential to increase the attractiveness of travel destinations and meet the changing needs of tourists. This adaptation is particularly important in regions with seasonal tourism, where infrastructure must be able to scale up or down based on the number of visitors (Sæþórsdóttir et al., 2019).

Adapting tourist infrastructure is necessary to respond to fluctuations in visitor numbers. Chow and Tsui (2019) point out that well-developed transport infrastructure, such as land and river ports, can significantly increase visitor numbers. Their study of incoming Russian visitors to China shows how adaptive infrastructure can respond to changing tourism dynamics, thereby increasing the reach and attractiveness of places.

The growing focus on accessible tourism requires that infrastructure be designed to accommodate all visitors, including those with disabilities. Ferreira et al. (2022) highlight the importance of adapting infrastructure to ensure it is fully accessible, thereby tapping into a significant market segment. Their findings indicate that stakeholder collaboration is vital to creating an inclusive tourism environment.

Effective management of tourism infrastructure requires strategic planning that accounts for the long-term consequences of visitor flows. Thaha et al. (2022) discuss the beach tourism value chain, noting that infrastructure development must include ancillary facilities, such as paved roads, to improve the visitor experience and accessibility. This approach underscores the need for comprehensive planning to ensure infrastructure can adapt to tourists' changing needs.

Understanding visitors' needs is crucial for adapting infrastructure. Kičić et al. (2020) studied the Grmoščica forest park and found that visitors requested additional infrastructure, such as trash cans and seating. These findings underscore the importance of adapting existing facilities to meet visitors' expectations and improve their overall experience.

Sufa et al. (2024) highlight the role of tourism infrastructure mediation in shaping visitor satisfaction and intention to return. The study shows that high-quality infrastructure not only attracts tourists but also shapes their overall experience, which is crucial for repeat visits.

Nguyen (2021) studies the relationship between investment in tourism infrastructure and attracting international visitors. The study shows that well-planned infrastructure investments can support sustainable tourism development, improving both visitor satisfaction and the local economy.

In summary, developing adaptable infrastructure is important for enhancing tourism experience and ensuring sustainability. By considering these aspects, tourism sites can better manage visitor flows and improve overall satisfaction.

2.2.3. Management strategies

Effective management strategies are key to reducing congestion and ensuring a sustainable tourism experience. The literature indicates that active management methods, such as installing reservation systems and monitoring visitor flows, can significantly reduce congestion in popular places. According to Zhu et al. (2022), it is important to examine how effective management strategies aimed at addressing visitor concentrations during holidays can influence peak travel avoidance behavior. In addition, Chen and Liang (2020) offer a predictive model of tourist flow that incorporates external factors such as weather and holidays to help managers anticipate and respond to changes in visitor patterns. Shymanskyi et al. (2022) highlight the importance of understanding global tourist flows and the factors that determine them, e.g., income levels and government policies, which can inform management strategies to increase the competitiveness of travel destinations. Integrating these strategies is essential to creating a balanced approach to tourism that takes into account both visitor satisfaction and the sustainability of the destination.

In summary, effective management strategies, including booking systems and visitor flow monitoring, are essential to reduce congestion and ensure a sustainable tourism experience. By understanding visitor behavior and factors that influence tourist flows, destinations can implement strategies that increase visitor satisfaction and promote sustainability. Integrating these methods is vital to creating a balanced tourism environment that benefits both visitors and local communities.

2.2.4. Seasonality and its effects

Seasonality is one of the most important factors in infrastructure congestion. Seasonality influences the economy and infrastructure use (Baum & Lundtorp, 2001). Yin et al. (2019) analyzed how transport infrastructure can affect tourism patterns, including seasonal effects. Nguyen (2021) discussed the relationship between investment in tourism infrastructure and seasonal visitor attraction, highlighting the need for adaptable infrastructure.

Butler (2001) discusses various models of tourism seasonality, including the impact on infrastructure and resource management. The Butler model is the basis for understanding how tourist demand fluctuates throughout the year. Baum and Lundtorp (2001) review tourism seasonality, discussing its economic impact and how it affects infrastructure use. The authors also discuss the challenges posed by seasonal fluctuations in visitor numbers. The paper by González et al. (2008) focuses on mobility models and provides insights into how seasonal tourism affects visitor flows and infrastructure needs.

Seasonality is one factor affecting infrastructure congestion in tourism. Understanding seasonality patterns and impacts is critical to effective tourism management and infrastructure planning. Therefore, understanding seasonality in tourism and its impact on infrastructure management is important. By examining seasonality patterns, measurement methods, and interactions with dynamic factors such as climate change, stakeholders can develop more effective strategies to manage infrastructure congestion and improve the overall tourism experience.

2.2.5. The role of events in tourism

Events play a very important role in the tourism sector. The literature indicates that both large- and small-scale events can increase the competitiveness of tourist destinations by attracting visitors. Cibinskiene (2012) emphasizes that events are an integral part of cities' marketing strategies, as they motivate tourism and contribute to the competitiveness of the overall destination.

Drakakis et al. (2021) emphasize that sporting events can drive economic recovery in host cities, underscoring their impact on local communities. According to the authors, strategic event management is essential to maximize these benefits (Chersulich Tomino et al., 2020). Pappa et al. (2022) report that stakeholder

perceptions of events can significantly affect the long-term sustainability of tourism destinations. Csobán and Serra (2014) also note the importance of aligning events with local infrastructure and cultural capital, advocating small-scale events as a strategy for developing sustainable tourism.

However, events can have negative impacts. They can also cause difficulties, especially after crises. Duan and colleagues provide a systematic overview of how tourism crises can destabilize the local economy and community well-being, noting that their effects can persist long after the events end (Duan et al., 2022).

In summary, events are multifaceted components of the tourism industry that can drive economic growth, increase community engagement, and contribute to destination branding. However, careful management and strategic planning are essential to maximize their benefits and mitigate potential adverse effects.

The literature review indicates that dynamic factors play a significant role in managing tourist infrastructure. Fuzzy logic and other dynamic analysis methods can help develop more efficient management strategies, but they need additional empirical research and integrated approaches.

2.3. Fuzzy logic and dynamical systems modeling

Fuzzy logic is one of the most promising methods for modeling uncertainty and dynamic systems. Scientific papers (Zadeh, 1965; Mendel, 2001) emphasize that fuzzy logic techniques are particularly appropriate in the tourism sector, where many factors are difficult to quantify.

Fuzzy logic is a promising methodology for modeling uncertainty and dynamic systems. The scientific literature highlights its suitability for the tourism sector, where many factors are difficult to quantify. Zadeh (1965) introduced fuzzy logic to address uncertainty in real-world problems, and Mendel (2001) expanded its application to various fields, including tourism (Tan & Chua, 2007). Thalmeiner et al. (2021) demonstrated fuzzy logic's use in assessing the COVID-19 pandemic's economic impact on tourism, showing its effectiveness in handling uncertainty. Xu et al. (2023) used a fuzzy multi-criteria decision-making model to assess the sustainability of mountain tourism, demonstrating fuzzy logic's applicability in evaluating complex tourism scenarios. Nilashi et al. (2022) discussed using fuzzy logic to address data scarcity in travel recommendation systems, highlighting its potential to improve consumer experience in tourism. Ullah et al. (2016) assessed the feasibility of community ecotourism using fuzzy logic analysis, demonstrating its effectiveness in evaluating qualitative tourism factors. According to de Paula et al. (2021), fuzzy logic supports decision-making in sustainable tourism, illustrating its usefulness in managing complex tourism environments.

Fuzzy logic provides a solid foundation for modeling uncertainty and addressing the complexities inherent in the tourism sector. By applying fuzzy logic methodologies, stakeholders can better navigate dynamic systems and improve decision-making. The references above illustrate fuzzy logic's versatility and effectiveness across various tourism-related applications, reinforcing its importance in modern tourism management.

2.4. Theoretical assumption

Based on literature, dynamic factors can control the load on tourist infrastructure. The mathematical assumption for managing the load on tourist infrastructure is:

$$A(t) = \frac{k_0 * T * S(t) * R(t) * (b_0 - a_0)}{A}; \quad (1)$$

Where: k_0 – tourist flow rate coefficient, T - number of tourists, S - influence of seasonality, R - influence of events, a_0 – coefficient of the amount of outgoing tourists, b_0 - coefficient of the amount of incoming tourists, A - capacity of tourist infrastructure, t -time.

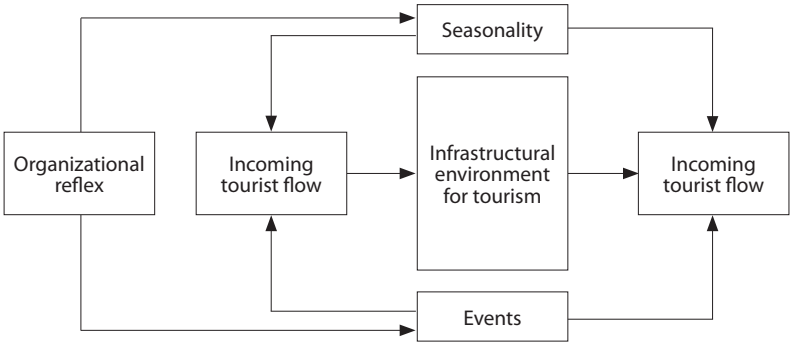
2.5. Tourist infrastructure congestion management model

The tourist infrastructure congestion management model was compiled using organizational reflex to create a decision-making model in which organizational reflex serves as a regulatory mechanism. Figure 1 shows the model. In an organization, organizational reflex is defined by two responses that are manifested from the information received from the environment, i.e., 1) a conditioned reflex, which is equated to a creative response in an organization, as a result of the interaction of specific knowledge and skills, where a competitive response to incoming information from the global environment is formed, and 2) an unconditional reflex, which corresponds to a routine response in an organization, as a competitive response formed by standard decisions to incoming information from the global environment.

Vaitkevicius et al. (2021) provided a model for how an organization's human resources respond to signals from the global environment. Analysis of the organization's responses to signals from the global environment and to the system's activity indicated that the organization functions much like the human reflex arc. This insight made it possible to recognize the structure of the human nervous system as a component of the organization's decision-making system.

The organization manipulates factors (seasonality and events) using managerial methods.

Figure 1
Tourist infrastructure management model



3. Strategic application of methods to build a model

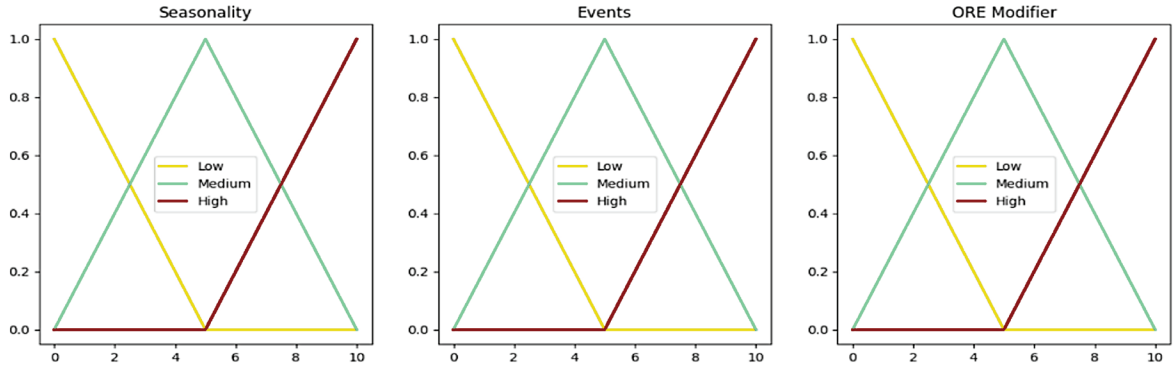
Theoretical modeling of the system that manages tourist flows was carried out using the following methods: 1) analogy; 2) comparison; 3) deduction; 4) extrapolation. This approach made it possible to predict the course of events in the global environment and apply these insights to the processes of decision-making and the optimization of the organization's activities.

Using these methods, a theoretical framework has been developed that enables the organization to adapt dynamically to changes in the global environment, effectively manage tourism flows, and ensure competitiveness.

Computer simulation. Membership functions for all three variables were defined using triangular functions, as shown in Figure 2. The graphs in Figure 2 (a-c) illustrate how fuzzy logic classifies seasonality and event data into "low", "medium", and "high" categories.

The organizational reflex modifier (hereinafter, ORE) is adjusted based on the data, determining the final efficiency. The overlap of curves illustrates the essence of fuzzy logic: a value can belong to several categories at once (see Figure 2). Each graph represents a fuzzy logic variable, where the degree of membership (0 to 1) indicates how strongly a value belongs to a category. More details are provided in Table 1.

Figure 2
Fuzzy logic membership function graphs: a) seasonality, b) events, c) organizational reflex effect modifier



Each input variable is defined by linguistic values (Low, Medium, High), each with a triangular membership function. The membership function $\mu(x) \in [0, 1]$ indicates the degree to which a value x belongs to a particular linguistic category.

The "If–Then" rules are presented in Table 1, which models the dependence between the input factors and the ORE modifier. In the fuzzification stage, membership degrees are calculated for each input value using triangular functions. The inference system applies all the rules based on these membership degrees and derives the output membership degrees. Finally, defuzzification yields the final size of the ORE modifier estimate.

Table 1
Fuzzy logic variables and rules

Fuzzy logic variables:		**a) seasonality**	**b) events**	**c) ORE modifier**
Axles	X axis	seasonality level (low to high seasonality of tourism)	intensity of events (low to high)	size of modification of organizational reflex efficiency (ORE)
	Y axis	degree of membership function (0 to 1), showing how strongly a given value belongs to a category		
Curves	"Low" (0-5)	off-season (low tourist flow)	little or no events	low impact on efficiency
	"Medium" (0-10)	transition period between season and off-season;	average amount of events	medium impact
	"High" (5-10)	peak season (large flow of tourists)	many large-scale events	strong impact on efficiency
For example,		if the seasonality value is 3, it will be strongly dependent on "Low" seasonality, but will also have a small dependence on "Medium"	if the intensity of the events is 6, the value can belong to both the "Medium" and "High" levels, i.e., the impact of the events on the system is significant, but not extreme	If seasonality and events are high, the fuzzy system will assign the ORE modifier to the "High" range, i.e., the efficiency will increase more
Fuzzy rule base „If–Then"	*Rule No.*	**IF**	**AND**	**THEN**
	R1	Low	Low	Low
	R2	Low	Medium	Medium
	R3	Low	High	Medium
	R4	Medium	Low	Medium
	R5	Medium	Medium	Medium
	R6	Medium	High	High
	R7	High	Low	Medium
	R8	High	Medium	High
	R9	High	High	High
For example,		IF seasonality is High AND events is High THEN ORE modifier is High. This rule reflects the need for stronger organizational reflexes in peak-demand situations with many large-scale events		

Fuzzy set formalization of seasonality and events impact on Organizational Reflex

For each variable, three linguistic terms are defined: Low, Medium, and High. Triangular membership functions are used, defined as:

$$\mu_{Low}(x) = \begin{cases} 1, \wedge\, x \le a \\ \frac{b-x}{b-a}, \wedge\, a < x < b \\ 0, \wedge\, x \ge b \end{cases}; \tag{2}$$

$$\mu_{Medium}(x) = \begin{cases} 0, \wedge\, x \le a \vee x \ge c \\ \frac{x-a}{b-a}, \wedge\, a < x \le b \\ \frac{c-x}{c-b}, \wedge\, b < x < c \end{cases}; \tag{3}$$

$$\mu_{High}(x) = \begin{cases} 0, \wedge\, x \le a \\ \frac{x-a}{b-a}, \wedge\, a < x < b \\ 1, \wedge\, x \ge b \end{cases} \tag{4}$$

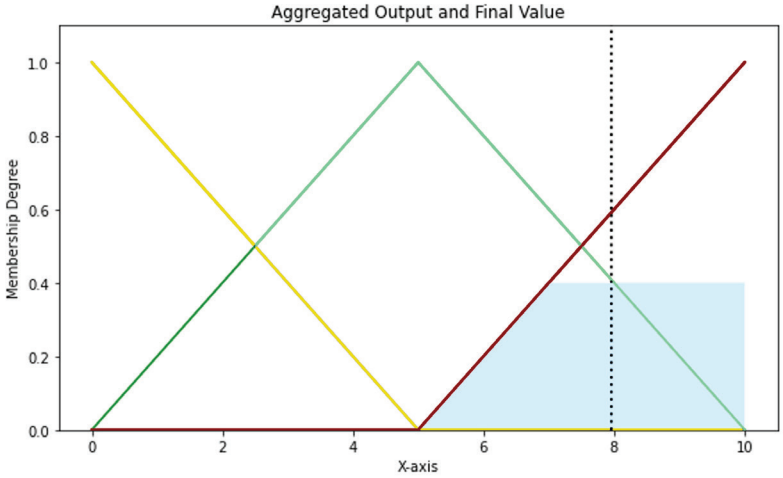
The parameters (a, b, c) for each variable are calibrated using historical tourism data from selected destinations (see Table 2).

Table 2
Parameters of triangular membership functions for input and output variables

Variable	Term	*a*	*b*	*c*
Seasonality (S)	Low	0.0	0.0	5.0
	Medium	0.0	5.0	10.0
	High	5.0	10.0	10.0
Events €	Low	0.0	0.0	5.0
	Medium	0.0	5.0	10.0
	High	5.0	10.0	10.0
ORE Modifier	Low	0.0	0.0	5.0
	Medium	0.0	5.0	10.0
	High	5.0	10.0	10.0

The results of the fuzzy logic simulation (see Figure 3) show that the aggregated area reflects the combination of output membership functions such as "Low," "Medium," and "High," obtained according to the fuzzy rules. The final value (in this case, 0.79) is determined by the centroid method, which optimally represents the entire aggregated fuzzy set. This value is a creative solution of the model, indicating how precisely the efficiency of the organizational reflex should be adjusted to manage the flow of tourists and avoid overloading the infrastructure.

Figure 3
Fuzzy output aggregation and defuzzification for ORE modifier



For example, if the model, based on fuzzy logic, calculates that the ORE should be 60.10 % instead of 46.84 %, this indicates that the system is more sensitive to changes and can respond more accurately to tourist flow dynamics, thereby increasing overall efficiency by 28.3 %. This helps better manage infrastructure and avoid both congestion and resource waste.

Inference process. The Mamdani method used the minimum operator for fuzzy implication and the maximum operator for aggregation. Defuzzification used the centroid (center of gravity) method.

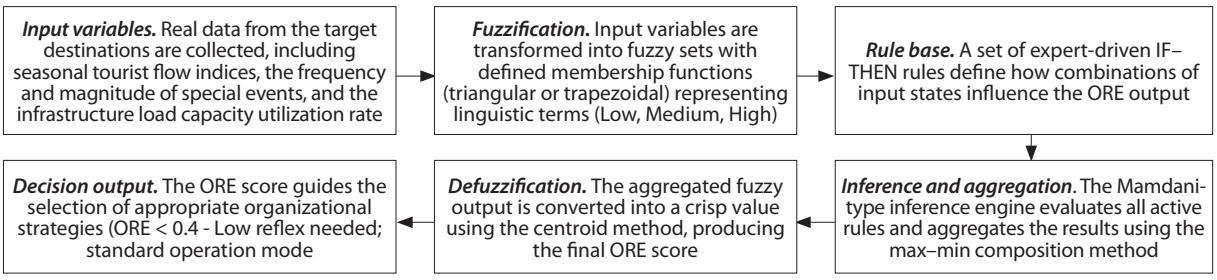
$$ORE = \frac{\int_{\Omega} \mu_{ORE}(y) \cdot y dy}{\int_{\Omega} \mu_{ORE}(y) dy} \tag{5}$$

where $\mu_{ORE}(y)$ is the aggregated membership function of the output variable, and Ω is the output domain [0,1] [0,1] [0,1].

Example of inference. When performing the calculation with S = 6.5 and E = 7.0, the fuzzy system assigns values to the membership functions, applies the rule base, and performs aggregation and centroid defuzzification. The resulting ORE = 0.73 indicates a high level of organizational reflex activity. The calculations were performed in the Python environment using the scikit-fuzzy library.

Structure of the decision-making model. The decision-making model employs a fuzzy inference system (FIS) to evaluate the Organizational Reflex Efficiency (ORE) in tourism infrastructure management. The model is designed to integrate multiple dynamic factors, including seasonality (S) and events (E), and translate them into actionable decision outputs.

Figure 4
Fuzzy decision-making framework



This modular architecture facilitates reproducibility and can be extended by adding further input variables (e.g., infrastructure capacity utilization, real-time sensor feeds) or by weighting rules based on empirical calibration.

An example of applying the model to real-world data. The seasonality indicator is assessed using hotel occupancy and tourist arrivals. Events are evaluated based on the number and scale of events on the calendar — festivals, concerts, fairs.

Fuzzification. Seasonality (9) ⟶ High membership ≈ 1.0. Events (7) ⟶ Medium ≈ 0.5; High ≈ 0.5. Rule activation. Rules 8 and 9 are active (High seasonality; Medium/High events). Activity level by min (membership values). Aggregation. A fuzzy output is obtained – the ORE modifier from the High area. Defuzzification. The result is ORE ≈ 7.5–8.0.

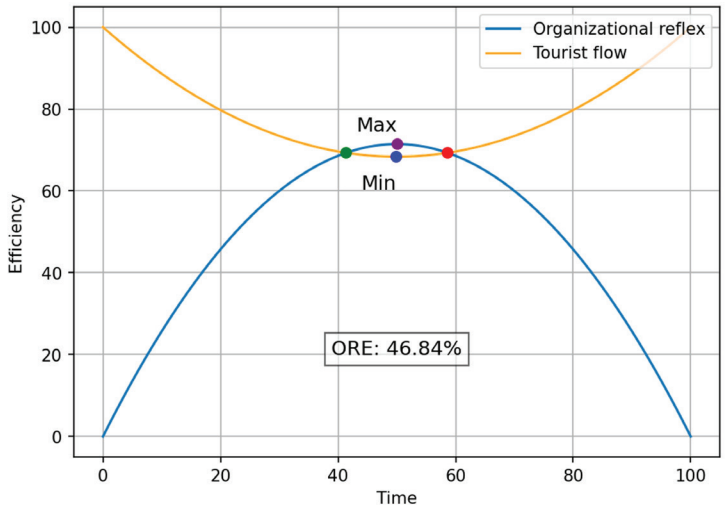
The model predicts that during peak season, the need for organizational reflex is high; therefore, additional management measures are required (personnel, service expansion, infrastructure load regulation).

4. Model computer simulation results

The performance of the prepared model is evaluated through computer simulation. To carry out the study, a computer simulator was developed to verify the operation of the compiled model using Anaconda Distribution program packages and designations (see Figure 5).

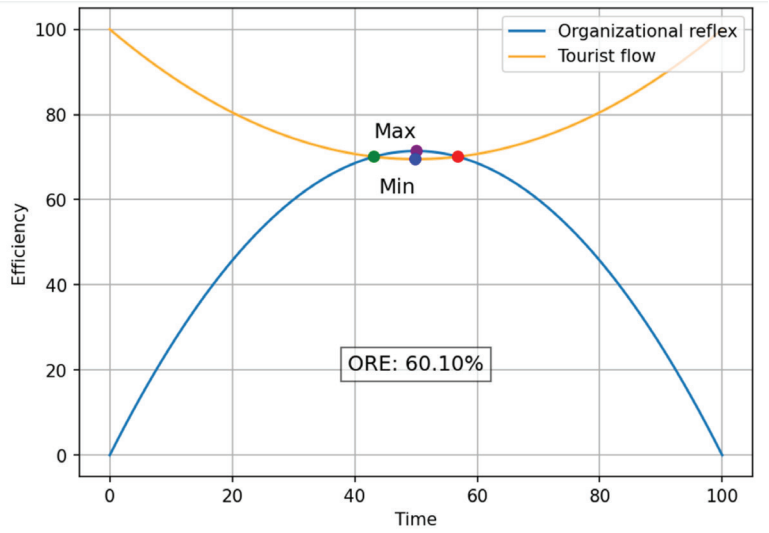
To theoretically evaluate the performance of the compiled model, we performed computer modeling to determine its behavior. The reaction of the model is observed and presented graphically in separate stages.

Figure 5
Organizational reflex efficiency (first stage)



At the initial stage, the model's efficiency in managing tourist flows was 46.84% (Figure 5). The initial intersection point of the organizational reflex (marked in green) indicates the moment of formation of the tourist flow and the "creative response". The point of maximum efficiency (Max) marks the formation of a solution, after which the tourist flow begins to increase again (this is reflected in the point of minimum intensity (Min)). The second intersection point (marked in red) indicates the end of the "creative process", after which the model's response is fully optimized and, with the help of the "routine process", the tourist flow is returned to the initial stage.

Figure 6
Organizational reflex efficiency (second stage)



The model's efficiency is increased by further integrating information generated by the model itself, finding a "creative solution" at the initial stage (Figure 6). The simulation results showed that after applying additional factors (additional information), the model's efficiency increased to 60.10% in managing tourist flows. The initial intersection point of the organizational reflex (marked in green) indicates the process of forming a "creative response". The point of maximum efficiency (Max) indicates the formation of a solution, after which tourist flow begins to increase again (as reflected in the point of minimum intensity (Min)). The second intersection point (marked in red) marks the end of the "creative process"; after this, the model's response becomes fully optimized and, with the help of the "routine process", tourist flow returns to the initial stage.

In summary, the analysis found that the initial organizational reflex efficiency (ORE) was 46.84%. After applying the model's solutions to the original case, which addressed seasonality and event effects, the model's efficiency increased to 60.10%. This indicates a 28.3% increase in efficiency. These results confirm that organizational reflexivity can significantly help optimize the load on tourist infrastructure and improve flow management.

5. Discussion

This study contributes to tourism management theory by integrating analyses of how dynamic factors affect infrastructure with the principles of organizational reflexivity and fuzzy logic, drawing on the works of Xu et al. (2023), Nilashi et al. (2022), and Vaitkevicius et al. (2021). It extends traditional life cycle models of carrying capacity and tourism (Mathieson & Wall, 1982; Butler, 1980) by incorporating real-time data analysis and the need for adaptive management strategies (Sæþórsdóttir et al., 2019). The study also offers a new perspective on how GIS systems and artificial intelligence can better explain visitor distribution and optimize infrastructure planning (Boers & Cottrell, 2007). This integration provides a solid theoretical framework for understanding the complex processes of managing visitor flows and ensuring sustainable tourism development, as Cucculelli and Goffi (2016) and Apriyanti (2024) note.

This study has significant practical implications for tourism policy makers, infrastructure planners, and tourism service providers. First, it emphasizes the need to move from static, predictive models to dynamic, adaptive management strategies that take into account seasonal fluctuations, the influence of events (Pappa et al., 2022; Drakakis et al., 2021) and other dynamic factors (Prideaux, 2005). Second, the study encourages

investment in real-time data analysis systems, GIS technologies, and artificial intelligence solutions that enable more efficient forecasting and management of tourist flows (Bertocchi et al., 2020). Third, it notes the importance of infrastructure adaptability (Chow & Tsui, 2019; Ferreira et al., 2022), emphasizing the need to create flexible and accessible tourism spaces that meet the needs of diverse groups of visitors, including those with disabilities (Smith et al., 2014). Finally, the study emphasizes integrating sustainability strategies to ensure infrastructure management not only improves the visitor experience (Sufa et al., 2024) but also reduces negative impacts on the environment and local communities (Cucculelli & Goffi, 2016).

This study has several limitations. First, a literature review may not capture all important publications, especially those published in lesser-known sources or available only in certain languages. Second, the study relies mainly on existing research and theoretical models (Butler, 1980; Mathieson & Wall, 1982), so it lacks empirical data from real-world case analysis. Third, the scope of the study is quite broad, so a deeper analysis of specific dynamic factors (Prideaux, 2005) or infrastructure management strategies (Hall, 2008; Page, 2019) is limited. Finally, the results of the study can be applied to different tourist areas to a limited extent, given their unique geographical, cultural and economic contexts.

Future research should prioritize collecting and analyzing empirical data to confirm and extend the study's findings. First, case studies should examine successful and unsuccessful infrastructure congestion management practices across diverse tourist destinations (Bertocchi et al., 2020). Second, quantitative models should be developed and tested to predict tourist flows and assess the effectiveness of different management strategies (Gonzalez et al., 2008). Third, future research should place greater emphasis on analyzing the impacts of specific dynamic factors (climate change, technological innovation, socioeconomic change) (Shymanskyi et al., 2022) and on developing specialized management solutions (Dredge et al., 2016). Finally, interdisciplinary research involving experts in tourism, geography, economics, information technology, and the environment is recommended to develop comprehensive and sustainable infrastructure management solutions (Boers & Cottrell, 2007).

Declaration of Competing Interests

The authors declare that they have no known competing interests that could have appeared to influence the work reported in this paper.

References

Apriyanti, M. E., Sumaryoto, & Meirinaldi. (2024). The importance of tourism infrastructure in increasing domestic and international tourism. *International Journal of Research in Vocational Studies (IJRVOCAS), 3*(4), 113-122. https://doi.org/10.53893/ijrvocas.v3i4.46

Baum, T., & Lundtorp, S. (Eds.). (2001). *Seasonality in tourism.* Elsevier.

Bertocchi, D., Camatti, N., Giove, S., & van der Borg, J. (2020). Venice and overtourism: Simulating sustainable development scenarios through a tourism carrying capacity model. *Sustainability, 12*(2), Article 512. https://doi.org/10.3390/su12020512

Boers, B., & Cottrell, S. (2007). Sustainable tourism infrastructure planning: A GIS-supported approach. *Tourism Geographies, 9*(1), 1-21. https://doi.org/10.1080/14616680601092824

Bramwell, B., & Lane, B. (2011). Critical research on the governance of tourism and sustainability. *Journal of Sustainable Tourism, 19*(4-5), 411-421. https://doi.org/10.1080/09669582.2011.580586

Butler, R. W. (1980). The concept of a tourist area cycle of evolution: Implications for management of resources. *The Canadian Geographer / Le Géographe Canadien, 24*(1), 5–12. https://doi.org/10.1111/j.1541-0064.1980.tb00970.x

Butler, R. W. (2001). Seasonality in tourism: Issues and implications. In T. Baum & S. Lundtorp (Eds.), *Seasonality in tourism* (pp. 5–22). Pergamon.

Chau, T. M. (2023). Empirical evidence in An Giang province about the results of assessing factors affecting tourism destination satisfaction. *GeoJournal of Tourism and Geosites, 50*(4), 1382-1389. https://doi.org/10.30892/gtg.50419-1137

Chen, N., & Liang, Y. (2020). A tourist flow prediction model for scenic areas based on particle swarm optimization of neural network. *Revue d'Intelligence Artificielle, 34*(4), 395–402. https://doi.org/10.18280/ria.340403

Chersulich Tomino, A., Perić, M., & Wise, N. (2020). Assessing and considering the wider impacts of sport-tourism events: A research agenda review of sustainability and strategic planning elements. *Sustainability, 12*(11), Article 4473. https://doi.org/10.3390/su12114473

Chow, C. K. W., & Tsui, W. H. K. (2019). Cross-border tourism: Case study of inbound Russian visitor arrivals to China. *International Journal of Tourism Research, 21*(5), 693-711. https://doi.org/10.1002/jtr.2297

Cibinskiene, A. (2012). Impact evaluation of events as factors of city tourism competitiveness. *Economics and Management, 17*(4), 1333-1339. https://doi.org/10.5755/j01.em.17.4.2997

Csobán, K. V., & Serra, G. (2014). The role of small-scale sports events in developing sustainable sport tourism–a case study of fencing. *Applied Studies in Agribusiness and Commerce, 8*(4), 17-22. https://doi.org/10.19041/APSTRACT/2014/4/3

Cucculelli, M., & Goffi, G. (2016). Does sustainability enhance tourism destination competitiveness? Evidence from Italian destinations of excellence. *Journal of Cleaner Production, 111*, 370-382. https://doi.org/10.1016/j.jclepro.2014.12.069

de Paula, L. B., Gil-Lafuente, A. M., & Alvares, D. F. (2021). A contribution of fuzzy logic to sustainable tourism through a case analysis in Brazil. *Journal of Intelligent & Fuzzy Systems, 40*(2), 1851-1864. https://doi.org/10.3233/JIFS-189191

Drakakis, P., Papadaskalopoulos, A., & Lagos, D. (2021). Multipliers and impacts of active sport tourism in the Greek region of Messinia. *Tourism Economics, 27*(3), 527-547. https://doi.org/10.1177/1354816620902328

Dredge, D., Jenkins, J., & Whitford, M. (2016). Tourism planning and policy: Historical development and contemporary challenges. In D. Dredge & J. Jenkins (Eds.), *Stories of practice: Tourism policy and planning* (pp. 13–35). Routledge.

Duan, J., Xie, C., & Morrison, A. M. (2022). Tourism crises and impacts on destinations: A systematic review of the tourism and hospitality literature. *Journal of Hospitality & Tourism Research, 46*(4), 667-695. https://doi.org/10.1177/1096348021994194

Ferreira, F., Liberato, D., Liberato, P., & Coentrão, R. (2022). Fostering accessible tourism: Stakeholders' perspective in Vila do Conde and Póvoa de Varzim. *International Conference on Tourism Research, 15*(1), 192–199. https://doi.org/10.34190/ictr.15.1.131

Gonzalez, M. C., Hidalgo, C. A., & Barabási, A.-L. (2008). Understanding individual human mobility patterns. *Nature, 453*(7196), 779-782. https://doi.org/10.1038/nature06958

Hall, C. M. (2008). *Tourism planning: Policies, processes and relationships* (2nd ed.). Pearson Education.

Kičić, M., Marin, A. M., Vuletić, D., Kaliger, I., Matošević, N., Šimpraga, S., & Krajter Ostoić, S. (2020). Who are the visitors of Forest Park Grmoščica and what are their needs? Results of quantitative exploratory survey. *South-East European Forestry: SEEFOR, 11*(2), 169–180. https://doi.org/10.15177/seefor.20-19

Mathieson, A., & Wall, G. (1982). *Tourism: Economic, physical, and social impacts*. Longman.

Mendel, J. M. (2001). *Uncertain rule-based fuzzy logic systems: Introduction and new directions*. Prentice Hall.

Mortazavi, R., & Cialani, C. (2017). International tourists' length of overnight stay in Venice. *Tourism Economics, 23*(4), 882-889. https://doi.org/10.5367/te.2016.0556

Nguyen, Q. H. (2021). Impact of investment in tourism infrastructure development on attracting international visitors: A nonlinear panel ARDL approach using Vietnam's data. *Economies, 9*(3), Article 131. https://doi.org/10.3390/economies9030131

Nilashi, M., Abumalloh, R. A., Alrizq, M., Almulihi, A., Alghamdi, O. A., Farooque, M., Samad, S., Mohd, S., & Ahmadi, H. (2022). A hybrid method to solve data sparsity in travel recommendation agents using fuzzy logic approach. *Mathematical Problems in Engineering, 2022,* Article 7372849. https://doi.org/10.1155/2022/7372849

Page, S. J. (2019). *Tourism management* (6th ed.). Routledge. https://doi.org/10.4324/9780429422898

Pappa, E., Didaskalou, E., Kontogeorgis, G., & Filos, I. (2022). Strategic management of tourism sustainability through the Greek stakeholders' perspective on the impacts of events: The case of Patras' Carnaval, Greece. *WIT Transactions on Ecology and the Environment, 256*, 85-95. https://doi.org/10.2495/ST220081

Prideaux, B. (2005). Factors affecting bilateral tourism flows. *Annals of Tourism Research, 32*(3), 780-801. https://doi.org/10.1016/j.annals.2004.04.008

Ritchie, J. B., & Crouch, G. I. (2003). *The competitive destination: A sustainable tourism perspective*. CABI.

Sæþórsdóttir, A. D., Hall, C. M., & Stefánsson, Þ. (2019). Senses by seasons: Tourists' perceptions depending on seasonality in popular nature destinations in Iceland. *Sustainability, 11*(11), Article 3059. https://doi.org/10.3390/su11113059

Salinas Fernández, J. A., Serdeira Azevedo, P., Martín Martín, J. M., & Rodríguez Martín, J. A. (2020). Determinants of tourism destination competitiveness in the countries most visited by international tourists: Proposal of a synthetic index. *Tourism Management Perspectives, 33*, Article 100582. https://doi.org/10.1016/j.tmp.2019.100582

Shymanskyi, O., Wang, J., & Pu, Y. (2022). Global tourist flows under the Belt and Road Initiative: A complex network analysis. *PLOS ONE, 17*(8), Article e0272964. https://doi.org/10.1371/journal.pone.0272964

Simón, F. J. G., Narangajavana, Y., & Marqués, D. P. (2004). Carrying capacity in the tourism industry: A case study of Hengistbury Head. *Tourism Management, 25*(2), 275-283. https://doi.org/10.1016/S0261-5177(03)00089-X

Skandali, D., & Tsourvakas, G. (2025). The underlying importance of value in artificial intelligent travel application acceptance model: Combining the value-based adoption model and the artificially intelligent device user acceptance theory. *Tourism: An International Interdisciplinary Journal, 73*(2), 326-339. https://doi.org/10.37741/t.73.2.11

Smith, A. J., Tuffin, M., Taplin, R. H., Moore, S. A., & Tonge, J. (2014). Visitor segmentation for a park system using research and managerial judgement. *Journal of Ecotourism, 13*(2-3), 93-109. https://doi.org/10.1080/14724049.2014.963112

Sufa, S. A., Setiawati, D., Afiat, M. N., & Rijal, S. (2024). The influence of tourism infrastructure and online promotion of tourist visit intention: Study on the Island of Bali with tourist satisfaction as an intervening variable. *International Journal of Business, Law, and Education, 5*(2), 1567-1576. https://doi.org/10.56442/ijble.v5i2.595

Tan, W. W., & Chua, T. W. (2007). Uncertain rule-based fuzzy logic systems: Introduction and new directions (Mendel, J. M.; 2001) [Book review]. *IEEE Computational Intelligence Magazine,* 2(1), 72-73. https://doi.org/10.1109/MCI.2007.357196

Thaha, F., Parakkasi, I., Sirajuddin, S., & Fathurrahman, R. A. (2022). Value-chain in beach tourism: The consideration of maslahah in strategic formulation. *Jurnal Minds: Manajemen Ide dan Inspirasi,* 9(2), 309-320. https://doi.org/10.24252/minds.v9i2.31584

Thalmeiner, G., Gáspár, S., Barta, Á., & Zéman, Z. (2021). Application of fuzzy logic to evaluate the economic impact of COVID-19: Case study of a project-oriented travel agency. *Sustainability, 13*(17), Article 9602. https://doi.org/10.3390/su13179602

Ullah, Z., Jehangir, M., & Iqbal, J. (2016). Potential for community based ecotourism (CBE) along Balochistan Coast, Pakistan. *Global Regional Review, 1*(1), 178-192. https://doi.org/10.31703/grr.2016(I-I).14

Vaitkevicius, S., Papsiene, P., & Vaitkevicius, J. V. (2021). Rethinking a timely response of human resources to global signals: A case of organizational reflexes. *Engineering Economics, 32*(1), 48-59. https://doi.org/10.5755/j01.ee.32.1.24199

Xu, M., Bai, C., Shi, L., Puška, A., Štilić, A., & Stević, Ž. (2023). Assessment of mountain tourism sustainability using integrated fuzzy MCDM model. *Sustainability, 15*(19), Article 14358. https://doi.org/10.3390/su151914358

Yin, P., Lin, Z., & Prideaux, B. (2019). The impact of high-speed railway on tourism spatial structures between two adjoining metropolitan cities in China: Beijing and Tianjin. *Journal of Transport Geography, 80*, Article 102495. https://doi.org/10.1016/j.jtrangeo.2019.102495

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X

Zhu, H., Guan, H., Han, Y., & Li, W. (2022). Study on peak travel avoidance behavior of car travelers during holidays. *Sustainability, 14*(17), Article 10744. https://doi.org/10.3390/su141710744

Submitted: March 27, 2025
Revised: May 13, 2026
Accepted: September 19, 2026

Appendix

Python code creates a Mamdani-type fuzzy logic model that helps transform subjective, vague data into concret and precise value and generates a visualization illustrating the entire process.

```
import numpy as np
import skfuzzy as fuzz
import matplotlib.pyplot as plt


def generate_fuzzy_model_graph(seasonality, events):
    """
    Generates a graph of the fuzzy logic model's inference process,
    based on given seasonality and events values.
    """
    # 1. Define fuzzy sets for input and output variables
    # All variables use a universal domain from 0 to 10.
    x_axis = np.arange(0, 10.1, 0.1)

    # Input variables' membership functions (triangular)
    low = fuzz.trimf(x_axis, [0, 0, 5])
    medium = fuzz.trimf(x_axis, [0, 5, 10])
    high = fuzz.trimf(x_axis, [5, 10, 10])

    # Output variable's membership functions (ORE Modifier)
    ore_low = fuzz.trimf(x_axis, [0, 0, 5])
    ore_medium = fuzz.trimf(x_axis, [0, 5, 10])
    ore_high = fuzz.trimf(x_axis, [5, 10, 10])

    # 2. Fuzzification: Determine membership degrees for given inputs
    s_low = fuzz.interp_membership(x_axis, low, seasonality)
    s_med = fuzz.interp_membership(x_axis, medium, seasonality)
    s_high = fuzz.interp_membership(x_axis, high, seasonality)

    e_low = fuzz.interp_membership(x_axis, low, events)
    e_med = fuzz.interp_membership(x_axis, medium, events)
    e_high = fuzz.interp_membership(x_axis, high, events)

    # 3. Rule Activation (using Mamdani method with minimum operator)
    # The result of np.fmin is now used to clip the output membership function arrays
    # R1: IF S is Low AND E is Low THEN ORE is High
    rule1_act = np.fmin(s_low, e_low)
    activated_low_R1 = np.fmin(rule1_act, ore_high)

    # R2: IF S is Low AND E is Medium THEN ORE is High
    rule2_act = np.fmin(s_low, e_med)
    activated_low_R2 = np.fmin(rule2_act, ore_high)
```

```
# R3: IF S is Low AND E is High THEN ORE is Medium
rule3_act = np.fmin(s_low, e_high)
activated_med_R3 = np.fmin(rule3_act, ore_medium)

# R4: IF S is Medium AND E is Low THEN ORE is Medium
rule4_act = np.fmin(s_med, e_low)
activated_med_R4 = np.fmin(rule4_act, ore_medium)

# R5: IF S is Medium AND E is Medium THEN ORE is Medium
rule5_act = np.fmin(s_med, e_med)
activated_med_R5 = np.fmin(rule5_act, ore_medium)

# R6: IF S is Medium AND E is High THEN ORE is Low
rule6_act = np.fmin(s_med, e_high)
activated_high_R6 = np.fmin(rule6_act, ore_low)

# R7: IF S is High AND E is Low THEN ORE is Medium
rule7_act = np.fmin(s_high, e_low)
activated_med_R7 = np.fmin(rule7_act, ore_medium)

# R8: IF S is High AND E is Medium THEN ORE is Low
rule8_act = np.fmin(s_high, e_med)
activated_high_R8 = np.fmin(rule8_act, ore_low)

# R9: IF S is High AND E is High THEN ORE is Low
rule9_act = np.fmin(s_high, e_high)
activated_high_R9 = np.fmin(rule9_act, ore_low)

# 4. Aggregation (using Mamdani method with maximum operator)
activated_ore_low = np.fmax(activated_high_R6, np.fmax(activated_high_R8, activated_high_R9))
activated_ore_medium = np.fmax(activated_med_R3, np.fmax(activated_med_R4,
np.fmax(activated_med_R5, activated_med_R7)))
activated_ore_high = np.fmax(activated_low_R1, activated_low_R2)

# Combine all activated outputs into a single aggregated membership function
aggregated = np.fmax(activated_ore_low, np.fmax(activated_ore_medium, activated_ore_high))

# 5. Defuzzification (Centroid method)
defuzzified_value = fuzz.defuzz(x_axis, aggregated, 'centroid')

# 6. Plotting
plt.figure(figsize=(8, 5))

# Plot original output membership functions with dashed lines
plt.plot(x_axis, ore_low, 'b--', linewidth=1, label='Low (orig)')
plt.plot(x_axis, ore_medium, 'g--', linewidth=1, label='Medium (orig)')
plt.plot(x_axis, ore_high, 'r--', linewidth=1, label='High (orig)')
```

```
# Plot the aggregated output as a filled area
plt.fill_between(x_axis, aggregated, 0, alpha=0.5, label='Aggregated output')
plt.plot(x_axis, aggregated, 'k', linewidth=2)

# Plot the defuzzified value as a vertical dotted line
plt.axvline(defuzzified_value, color='k', linestyle=':', linewidth=2, label=f'Centroid
= {defuzzified_value:.3f}')

plt.title('Aggregated Output and Defuzzified Result')
plt.xlabel('ORE Modifier')
plt.ylabel('Membership Degree')
plt.ylim(0, 1.1)
plt.legend()
plt.grid(True, linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()


# Example usage with S=6.5 and E=7.0
generate_fuzzy_model_graph(seasonality=6.5, events=7.0)
```