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A FUZZY MODEL FOR EVALUATING THE LEVEL OF TOURIST MOVEMENT TO INFRASTRUCTURE AND ACCESSIBILITY IN THE REGIONS

Beata Gavurova
E-mail: gavurova@utb.cz
ORCID: https://orcid.org/0000-0002-0606-879X
Affiliation: Faculty of Management and Economics, Tomas Bata University in Zlín, Czech Republic
ROR: https://ror.org/02j9z0y57

Volodymyr Polishchuk
E-mail: volodymyr.polishchuk@tuke.sk
ORCID: https://orcid.org/0000-0001-7609-2737
Affiliation 1: Faculty of Aeronautics, Technical University of Košice, Slovakia
ROR: https://ror.org/00yjd3n13

E-mail: volodymyr.polishchuk@tuke.sk
ORCID: https://orcid.org/0000-0001-7609-2737
Affiliation 2: Faculty of Information Technology, Uzhhorod National University, Ukraine
ROR: https://ror.org/02ryxbr72

Inna Polishchuk
E-mail: inna.polishchuk@tuke.sk
ORCID: https://orcid.org/0000-0002-0658-037X
Affiliation 1: Faculty of Aeronautics, Technical University of Košice, Slovakia
ROR: https://ror.org/00yjd3n13

E-mail: inna.polishchuk@tuke.sk
ORCID: https://orcid.org/0000-0002-0658-037X
Affiliation 2: Faculty of Information Technology, Uzhhorod National University, Ukraine
ROR: https://ror.org/02ryxbr72

Annotation. The issue of forecasting demand and researching its dimensions, including tourism infrastructure, has not yet been sufficiently explored. From the available studies, it can be concluded that the traditional theories of demand in tourism and the various model approaches are applied for its investigation. Therefore, a sufficient space is created for the improvement of techniques, approaches, methods, and tools that enable obtaining new outcomes for the decision-making processes and for the construction of policies. The main goal of this study was to develop a fuzzy model for evaluating the level of tourist movement to infrastructure and accessibility in the regions of the V4 countries, based on travel satisfaction relative to the expected and actual experience of participants in the tourist movement. For the first time, a model of fuzzy logical inference of level of travel satisfaction relative to expected and actual experience from infrastructure and accessibility is developed. The research results were tested, and the developed model was verified on real data from 2,343 participants of the tourist movement for the regions of the V4 countries. The effective policies and the efficient decision-making processes are one of the most important ways to eliminate the regional disparities and discrepancies impacting the economic, health, social, and environmental fields of each country.

Keywords: decision-making, hybrid model, expert knowledge, Fuzzy sets, Fuzzy logic inference, tourism, tourism infrastructure.

JEL classification: I12, I18, C02, C51, C55.

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Introduction

Tourism represents the most dynamic and the fastest developing service industry. Technological development, development of markets, destinations, and infrastructure also contribute significantly to its development. The globalisation trends, mass consumers, as well as the economic parameters significantly influence tourism. In many countries, it is considered the only tool for the development of a lagging area while maintaining the quality of its environment. From an economic point of view, tourism is the most extensive subject of business in the whole world. It represents a key export of services for many economies of the world. It significantly contributes to the labour market and regional economic development. The latest economic data show that in the Organisation for Economic Co-operation and Development member countries, tourism contributes to the creation of the gross domestic product by 4.7 %, by 6% to the creation of new labour positions, and by 21 % to the export of services (OECD, 2018). Concurrently, there are also research studies dealing with the issue of tourism sustainability along with its development.

Despite extensive research into the dimensions of tourism, a number of empirical and theoretical questions remain unresolved (Chen and Li, 2025; Raheem Ahmed *et al.,* 2024). These efforts are also complicated by the considerable heterogeneity of the tourism sector, the application of the current empirical methods and the techniques to different data sets, and insufficient consideration of the theoretical and empirical implications of the applied methods (Yu and Huarng, 2025; Hong *et al.,* 2025). A specific feature of a number of research studies is the fact that the analytical processes apply the data for a specific country or a group of countries, region, and destination (Wu *et al.,* 2017; Dinçer and Yüksel, 2019; Büyüközkan *et al.,* 2021). Very diverse population groups are also observed, or the population groups are vaguely defined (the whole population versus the employed part of the population) and are quite heterogeneous. Research studies do not sufficiently reflect the heterogeneity between the destinations, thereby considerably limiting the usability and interpretability of the results.

The preparation of a comparative platform is complex, as the influence of the various socio-economic factors, weather and economic cycles, cultural aspects, the political situation in the country, the level of security, and corruption play a role. The dynamic environment in tourism requires the creation of the analytical patterns, initiating the development of new empirical approaches to its investigation.

Tourism has historical, psychological, social, cultural, international, economic, political, environmental, and technological dimensions that support this sector in its development. An important part of these dimensions is the tourism infrastructure that directly affects the demand for tourism (But, 2024; Martín-Martín *et al.,* 2023). Several research teams have dealt with the issue of tourism demand analysis and forecasting. Their research studies point to the methodological problems (Jiao and Chen, 2019; Wong *et al.,* 2006; Claveria *et al.,* 2016), as well as progress in the development of methods, models, and approaches (Claveria *et al.,* 2016; Hu *et al.,* 2019; Shahrabi *et al.,* 2013; Cankurt and Subasi, 2015). They also point to the need for constant investigation of the methodological platform and testing the suitability and applicability of well-known as well as less well-known methods to achieve optimal results for decision-making processes not only at governmental level, but also at meso and micro levels of management.

Our research aims to support decision-making on the feasibility of improving accessibility and internal and external infrastructure to increase tourism in the regions of the V4 countries. Decision-making will be justified when it is based, among other things, on quantitative indicators. Therefore, the research determines the quantitative and linguistic level, using an innovative tool: intellectual analysis of the knowledge of the participants of the tourist movement. The research was conducted on real expert data, and considers the level of travel satisfaction relative to the expected and real experience of the participants of the tourist movement from infrastructure and accessibility. The main goal of this study is to develop a fuzzy model for evaluating the level of tourist movement in relation to infrastructure and accessibility in the regions of the V4 countries, based on travel satisfaction in relation to the expected and real experience of participants in the tourist movement.

The relevance of this study is confirmed by the European Data Strategy (Agbola *et al.,* 2020) for its implementation by 2030, with the aim of becoming a leading model in the EU to emulate a society endowed with data, to improve decisions, both in business and in the public sector. The scientific hypothesis of this study is formulated as follows: if in the selected region, the participants of the tourist movement have a high level of satisfaction with the trip relative to the expected and real experience in terms of infrastructure and accessibility, then it is possible to claim a high estimate of the level of tourist movement in this region. The results are based on the constructed fuzzy model, which takes into account the level of quality of tourist services and tourism development.

1. Literature Review

The global tourism industry experienced substantial growth until the onset of the year 2020 due to the technological progress and the globalisation processes. In its study, the Organisation for Economic Co-operation and Development (2018) identified the four megatrends that will shape the development of the tourism sector until 2040: the development of visitor demand, the growth of sustainable tourism, assistive technologies, and travel mobility. The tourism infrastructure is also related to these megatrends and is examined from many dimensions. The pandemic caused by COVID-19 has brought considerable uncertainty to the tourism sector, accompanied by negative economic as well as social impacts. This uncertainty was also accompanied by changes in institutional conditions in other sectors, as well as the behaviour and decision-making of tourists. This has created pressure for more intensive research into the drivers of tourism demand and the creation of new and effective strategies and policies (Agbola *et al.,* 2020). Understanding the factors influencing tourism demand is paramount for implementing structural economic changes, establishing regulatory and stabilisation mechanisms, particularly in nations where tourism development is pivotal to their economic viability. The increasing interconnectedness of people, cities and economies, which is a hallmark of globalisation processes, will render the understanding of the known more demanding, as well as the revelation of new factors influencing the demand for tourism. Researching the tourism sector as a system at national as well as international levels will be more demanding on the methodological apparatus. Decision-making processes are becoming increasingly complex due to changes in the external environment and will require the availability of extensive analytical outputs. Constant changes in the dynamic business environment will call for the need to investigate and uncover new determinants in the tourism industry and their causal links to create quality forecasting platforms.

The demand for tourism is strongly dependent on infrastructure. Numerous studies have identified the development of tourism infrastructure, income generation, distance and relative prices as pivotal factors in the development of a destination (Seetanah *et al.,* 2011; Lim *et al.,* 2019; Rosselló-Nadal and He, 2020; Gunter *et al.,* 2019). The development of the transport infrastructure can significantly influence the expenditure on tourism. An important role in the evaluation of these ties is played by a level of development of the countries (Ivankova *et al.,* 2021). The investigation of regional and geographical disparities and discrepancies in tourism is becoming part of strategy making at national as well as international levels. In the less developed countries, the development of transport infrastructure can also increase spending on tourism (Haller *et al.,* 2020; Kanwal *et al.,* 2020).

Transport infrastructure is also an important parameter in determining the attractiveness of destinations. It is an important part of the complex tourism infrastructure. Loi *et al.,* (2017) and Tosun *et al.,* (2015) consider the transport infrastructure to be an important determinant of the inflow of tourists to the destination. However, the impact of transport infrastructure is also determined by the origin of the destination (Khadaroo and Seetanah, 2008), as well as other macroeconomic and microeconomic factors. Ghalia *et al.,* (2019) applied a gravity model to investigate the impacts of institutional quality associated with the political risks, accessibility, and the socio-economic factors on the flow of tourists. According to the authors, institutional quality and the absence of conflicts are the main driving forces supporting the flow of tourism.

The importance of the gravity models is also emphasised by Morley *et al.,* (2024), who see their great importance in the tourism demand modelling processes. The authors discuss the appropriateness of an application of the latest versions of the gravity models as well as the aggregate demand models for the assessment and quantification of the structural factors in the tourism demand. The geographical aspects of tourism demand to open up the new evaluation dimensions, creating a space for an application of the known and as well as innovative analytical methods and models. This also introduces a space for an extensive multidisciplinary investigation of the issue (Massidda, Etzo, 2012; McKercher, Mak, 2019; Lorde *et al.,* 2016; Wong *et al.,* 2017).

Even though the forecasting methods in the tourism industry have been developed for several decades, no consensus has yet been reached, which types of the forecasting models tend to be more accurate, and in which circumstances they are more appropriate. Peng *et al.,* (2014) drew attention to this fact and applies the meta-analysis to examine the relationships between the accuracy of the different forecasting models. The results of the meta-regression analysis show that the destination, the origin of tourists, the time parameters, the available data interval, the number of variables, the sample size, and the modelling method are the important factors affecting the accuracy of the forecasting models. Until this period, it was the first study declaring an effort to match the forecasting models with the data characteristics and the forecasting context. Some authors have also investigated the issue of sustainable tourism infrastructure (Mamirkulova *et al.,* 2020; Lopes *et al.,* 2018; Mathew, Sreejesh, 2017). This prompted the need to develop causal models that allow specification of the direct and indirect links between the perceived tourism infrastructure, sustainable tourism development, and residents' perception of life quality. Peng *et al.,* (2015) aimed to examine the relationship among the estimated international tourism demand elasticities, the data characteristics, and the study features that may affect such empirical estimates. Applying the meta-regression analysis, the authors found that the time parameters, the origin of tourists, the destination, the data interval, the modelling method, the sample size, and inclusion or exclusion of the other explanatory variables significantly influence the estimates of the demand elasticities in the models.

Song and Li (2008) examined the application of methods for forecasting demand, and concluded that the methods applied in analyses and forecasting were much more different than the methods applied in solving other issues. The time series analyses, and the econometric models were most often applied. The authors concluded that there is no optimal model with the highest benefits. Jiao and Chen (2019) also confirm the popularity of the econometric time series, which began to be applied more intensively around the year 2007, but they see its greatest role in the position of the benchmarking models to measure performance and to compare with the new models. The authors have identified new trends in the inclusion of mixed frequency, the spatial regression, and the hybrid models. They also draw attention to the importance of the combination components and the combination techniques. In their study, Song *et al.,* (2019) mention that the prognosis models are currently more diversified and that accuracy of the predictions is constantly improving. Nevertheless, due to the high methodological demand and complexity of the quantification process of demand for tourism, it is not possible to determine a universal method.

The forecasting methods are being constantly developed, and the results that have been used by a combination of several methods are increasingly applied in the decision-making processes. Aslanargun *et al.* (2007) examined the benefits of different models of the artificial neural network and the hybrid models that are applied as the alternatives to the commonly applied autoregressive integrated moving average (ARIMA) models. The authors compared the outputs of the ARIMA, ANN, multilayer perceptron and radial basis function network models, as well as a combination of these models in solving the problem of the accurate forecasting of tourist arrivals to the observed destination. The models with nonlinear components give a better performance. As an optimal method in solving the research problem, Hadavandi *et al.* (2011) selected the hybrid artificial intelligence model to develop a Mamdani-type fuzzy rule-based system. The hybrid model applied the genetic algorithm for learning the rules and focuses on tuning the fuzzy system database. It was the first study that applied an approach based on genetic fuzzy systems for tourist arrival forecasting problem. The outcomes with a high level of accuracy have been achieved, so this approach can be considered a suitable for the tourist arrival forecasting problem.

Pai *et al.* (2014) highlight the advantages of the fuzzy models and the combined approaches for obtaining accurate results. The authors developed a novel forecasting system to accurately forecast tourism demand. Their new system consisted of a combination of fuzzy c-means with the logarithm least-squares support vector regression technologies. The genetic algorithms were optimally applied to select the parameters of the logarithm least-squares support vector regression. The results of the study declare obtaining more accurate results (prognoses) through the proposed prognostic system than the results obtained by the other methods. Atsalakis *et al.* (2018) presented a new approach to solving the forecasting issues in tourism by an application of a hybrid intelligence system called the Adaptive Neuro Fuzzy Inference System. This system combines both the learning capabilities of a neural network and the reasoning capabilities of fuzzy logic to give the enhanced forecasting capabilities. Greater benefits were expected as compared to an application of a single methodology itself. The outcomes of the analyses confirmed the fact that the Adaptive Neuro Fuzzy Inference System represents a unique system allowing to capture uncertainty in the relationships between the input and output variables. The comparative analysis of this approach with the other methodologies clearly confirms the superiority of the proposed approach.

Nilashi *et al.* (2015) also dealt with the issue of the personalised information for online users in the tourism industry. They describe the collaborative filtering techniques for a prediction of the information requirements in order to satisfy customers' needs to combat information overload in the hotel industry. The multicriteria collaborative filtering can define the precise recommendations based on the evaluation of the user preferences. The authors suggest an application of a new hybrid method through the dimensionality reduction and the prediction techniques. They developed a multi-criteria collaborative filtering system to increase prediction accuracy through the Gaussian mixture model with the Expectation-Maximisation Algorithm and the Adaptive Neuro-Fuzzy Inference System. The experimental outcomes confirmed the fact that the proposed hybrid method achieved high accuracy in solving the given problem in the tourism sector.

Based on the presented results of the research studies, their strong heterogeneity is apparent and is influenced by the geographical scope of the studies, as well as numerous sectoral specificities in the countries. The significant differentiation of the tourism sector, different sectoral policies in the countries, economic, social, cultural, geographical and environmental specifications of the regions, historical aspects, geopolitical situation, and globalisation influences will create the increasingly demanding analytical requirements for the decision-making mechanisms and the construction of the effective policies that will have a strong impact on the development of the systems aimed at increasing the competitiveness of the countries and the regions, as well as the economic, social, and environmental sustainability of sectors. For this reason, it is necessary to systematically investigate this issue from several dimensions and to network the research findings at an international level, which would help create a high-quality research platform and support the development of the methodologies and the systems of effective management and planning in the sectors.

2. Data and Methods

2.1 Formal Formulation of the Evaluation Problem

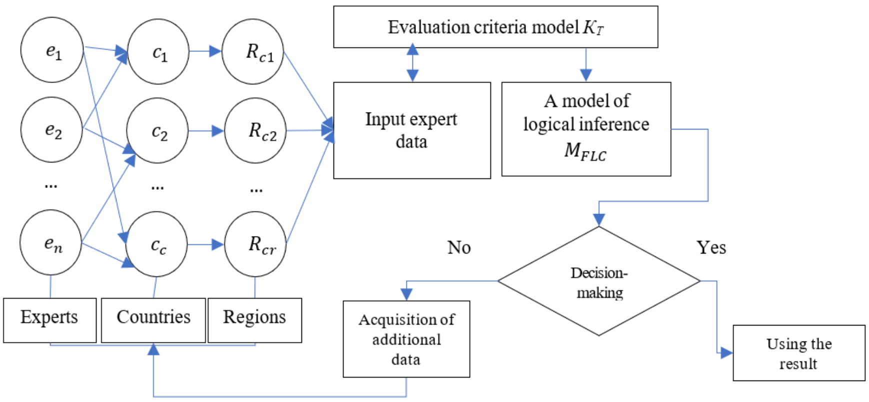
Let's consider $R_C = \{R_{C1}; R_{C2}; \ldots; R_{Cr}\}$ as a set of regions for evaluating the level of tourist movement in countries $C = \{c_1; c_2; \ldots; c_c\}$; $E = \{e_1; e_2; \ldots; e_n\}$, which is a set of experts (participants of the tourist movement) who assessed the level of internal and external infrastructure in the destination visited in the corresponding region of the country; K_T is the information model of criteria for evaluating the level of tourist movement in relation to infrastructure and accessibility; M_{FLC} is the model of fuzzy logical inference of level of travel satisfaction relative to expected and actual experience from infrastructure and accessibility. The system-theoretical-multiple model of the task of assessing the level of tourist movement concerning infrastructure and accessibility in the regions is presented as follows:

$\{C, R_C, \mathrm{E}, K_T, M_{FLC}, |Y(f)\}$.(1)

As a result, the initial estimate $Y(f) = \{m;\ \gamma\}$, which consists of m – a quantitative assessment of the level of tourist movement and a linguistic assessment γ of the interpretation of this level, is formulated. The initial assessment $Y(f)$ contains the content of the expediency of improving accessibility, and internal and external infrastructure in places of tourist movement, and on its basis, the degree of reasonableness of management decision-making regarding regional tourism support scenarios increases.

The subjects of management for the given expert task include *experts* who are participants of the tourist movement, who spoke about the expected and obtained real experience of visiting the destination. A *system analyst* is a person who collects information from experts and adjusts evaluation processes based on the proposed models, forms a set of evaluation criteria. A *decision-making person* (DM), persons (state authorities or local self-government bodies) who make further decisions on the feasibility of improving accessibility, internal and external infrastructure in places of tourist movement, based on the obtained initial assessment of the level of tourist movement.

The structural scheme of the fuzzy model for evaluating the level of tourist movement in relation to infrastructure and accessibility in the regions is illustrated in *Figure 1*.



Source: created by the authors.

Figure 1. **The Structural Scheme of the Fuzzy Model for Evaluating the Level of Tourist Movement**

Figure 1 shows a structural scheme for evaluating the level of traveler movement concerning infrastructure and accessibility in the regions. The assessment is followed by the adoption of the DM decision regarding the feasibility of improving accessibility and internal and external infrastructure in places of tourist movement, with the aim of increasing regional tourism. If the decision does not satisfy the DM, it is possible to revise the assessment or involve additional indicators and data for assessment. At the output, in order to increase the degree of reasonableness of management decision-making regarding regional tourism support scenarios, a quantitative assessment of the level of tourist movement, as well as a linguistic assessment of the interpretation of such a level that takes into account the region, the satisfaction of experts from the trip concerning the expected and real experience, linguistic analysts' opinions regarding the quality of tourist services, and the development of tourism in the evaluated region would have to be taken into consideration.

2.1 Information Model of Criteria for Evaluating the Level of Tourist Movement in Relation to Infrastructure and Accessibility

An information model for evaluating the level of tourist movement concerning infrastructure and accessibility isintroduced. This information model consists of two groups of criteria: G_1 – infrastructure and external accessibility and G_2 – infrastructure and internal accessibility. Consider the group of criteria G_1 – infrastructure and external accessibility. It consists of the following criteria: K_{11} – reliability of the booking service, K_{12} – reliable internet connection, K_{13} – safety in transport, K_{14} – availability of public toilets, and K_{15} – availability of physical security. For each of the criteria, the expert must give one linguistic answer $L_1 = \{EP_1;\ RP_1;\ EN_1;\ RN_1\}$ to questions about positive and negative aspects of infrastructure and external accessibility at the destination, relative to expected and actual experience, namely:

What POSITIVE aspects did you EXPECT/ASSUMED to experience in terms of infrastructure and internal accessibility in the destination you visited? The expert's answer: $EP_1(ep)$ ={Unexpected; Expected}.

What POSITIVE aspects did you actually EXPERIENCE in terms of infrastructure and internal accessibility in the destination you visited? The expert's answer: $RP_1(rp)$ ={Haven't experienced; Experienced}.

What NEGATIVE aspects did you EXPECT to experience in terms of infrastructure and internal accessibility in the destination you visited? The expert's answer: $EN_1(en)$ ={Unexpected; Expected}.

What NEGATIVE aspects did you actually EXPERIENCE in terms of infrastructure and internal accessibility in the destination you visited? The expert's answer: $RN_1(rn)$ ={Haven't experienced; Experienced}.

Consider the group of criteria G_2 – infrastructure and internal accessibility. This group of criteria includes the following: K_{21} – sufficiency of children's spaces, K_{22} – easy access to various cultural or entertainment facilities, K_{23} – availability of sufficient equipment for the disabled, K_{24} – accessibility to banking services (withdrawal of money), and K_{25} – level of environmental cleanliness. Similarly, for each of the criteria, the expert gives one linguistic answer $L_2 = \{EP_2;\ RP_2;\ EN_2;\ RN_2\}$ to questions about positive and negative aspects of infrastructure and internal accessibility at the destination, relative to expected and actual experience, namely:

What POSITIVE aspects did you EXPECT/ASSUMED to experience in terms of infrastructure and internal accessibility in the destination you visited? The expert's answer: $EP_2(ep)$ ={Unexpected; Expected}.

What POSITIVE aspects did you actually EXPERIENCE in terms of infrastructure and external accessibility in the destination you visited? The expert's answer: $RP_2(rp)$ ={ Haven't experienced; Experienced}.

What NEGATIVE aspects did you EXPECT to experience in terms of infrastructure and external accessibility in the destination you visited? The expert's answer: $EN_2(en)$ ={ Unexpected; Expected}.

What NEGATIVE aspects did you actually EXPERIENCE in terms of infrastructure and external accessibility in the destination you visited? The expert's answer: $RN_2(rn)$ ={ Haven't experienced; Experienced}.

To evaluate the accessibility of the region, the expert needs to answer the question according to the proposed evaluation criteria, choosing the option that is the closest to the truth in the context of the expected positive and negative aspects of the trip, and the actual positive and negative aspects, after the visit. Both the number of criteria groups and the sets of criteria are open. If necessary, the system analyst can always add other important indicators. As a result, after traveling in year ε, some region R_C of country C, input expert data from expert e_j will look as presented in *Table 1*, where $\left(EP_g\right)_{gk}^{j}$, $\left(RP_g\right)_{gk}^{j}$, $\left(EN_g\right)_{gk}^{j}$, and $\left(RN_g\right)_{gk}^{j}$ are linguistic evaluations of g – group of criteria, gk – criterion number, j – expert number, $g = \overline{1,2}$; $k = \overline{1,5}$; $j = \overline{1,n}$.

Table 1. Input Data from an Expert e_j.

Name criterion	Positive aspects		Negative aspects	
	Expected experience (ep)	Real experience (rp)	Expected experience (en)	Real experience (ep)
G_1 – infrastructure and external accessibility				
K_{11}	$(EP_1)_{11}^j$	$(RP_1)_{11}^j$	$(EN_1)_{11}^j$	$(RN_1)_{11}^j$
K_{12}	$(EP_1)_{12}^j$	$(RP_1)_{12}^j$	$(EN_1)_{12}^j$	$(RN_1)_{12}^j$
…	…	…	…	…
K_{15}	$(EP_1)_{15}^j$	$(RP_1)_{15}^j$	$(EN_1)_{15}^j$	$(RN_1)_{15}^j$
G_2 – infrastructure and internal accessibility				
K_{21}	$(EP_2)_{21}^j$	$(RP_2)_{21}^j$	$(EN_2)_{21}^j$	$(RN_2)_{21}^j$
K_{22}	$(EP_2)_{22}^j$	$(RP_2)_{22}^j$	$(EN_2)_{22}^j$	$(RN_2)_{22}^j$
…	…	…	…	…
K_{25}	$(EP_2)_{25}^j$	$(RP_2)_{25}^j$	$(EN_2)_{25}^j$	$(RN_2)_{25}^j$

Source: created by the authors.

The presented information model is not a benchmark for evaluating the level of tourist movement in relation to infrastructure and accessibility in the regions; it demonstrates the possibility of evaluation of real data.

2.2 Model of Fuzzy Logical Inference of Level of Travel Satisfaction Relative to Expecte and Actual Experience from Infrastructure and Accessibility

The mathematical model of fuzzy logical interference is based on the logical conclusion of the level, taking into account the psychological properties of human behaviour, when the expected does not correspond to reality. As expected, it is one of the strong regulators of individual behaviour. The expectation is a way to increase the subjective probability of an event, as opposed to the objective one. Expectation increases the motivational potential of an individual and increases cognitive activity, which in tourism leads to direct investment in the economy of the region. In turn, the discrepancy between expectations and real experience causes a “crisis of disappointment”, due to which there is a low probability of visiting the destination again, and the spread of negative reviews, which will reduce the number of new potential participants in the tourist movement. Therefore, the model of fuzzy logical inference for evaluation criteria is based on the intellectual analysis of knowledge of the subject area and takes into account the logic of the psychological properties of an individual’s behaviour.

At the first stage, the resulting quantitative evaluations are obtained for each group of evaluation criteria by using elements of fuzzy logic and psychology of the participants of the tourist movement regarding the expected and actual experience. At the second stage, an aggregated quantitative assessment of the level of travel satisfaction in relation to the expected and actual experience from the infrastructure and accessibility is built based on the received assessments for two groups of criteria.

Since all input linguistic evaluations can take on two values, then it is suggested to introduce the following characteristic functions for them:

$$\begin{cases} ep = \begin{cases} 1, & if \quad EP = \{\text{Expected}\}; \\ 0, & if \quad EP = \{\text{Unexpected}\}. \end{cases} \\ rp = \begin{cases} 1, & if \quad RP = \{\text{Experienced}\}; \\ 0, & if \quad RP = \{\text{Haven't experienced}\}. \end{cases} \\ en = \begin{cases} 1, & if \quad EN = \{\text{Expected}\}; \\ 0, & if \quad EN = \{\text{Unexpected}\}. \end{cases} \\ rn = \begin{cases} 1, & if \quad RN = \{\text{Experienced}\}; \\ 0, & if \quad RN = \{\text{Haven't experienced}\}. \end{cases} \end{cases} \qquad (2)$$

Where ep – evaluations for positive aspects regarding the expected experience, rp – evaluations for positive aspects regarding real experience, en – evaluations for negative aspects regarding the expected experience, and rn – evaluations for negative aspects relative to real experience.

The sum of the scored points is calculated against the groups of criteria, in the context of the expected positive and negative aspects of the trip and the actual positive and negative aspects after the visit:

$$\delta_j(l_g) = \sum_{k=1}^{5} (l_g)_{gk}^{j}. \qquad (3)$$

Where $l = \{ep;\ rp;\ en;\ rn\}$, $g = \overline{1,2}$; $j = \overline{1,n}$.

The following approach is proposed for deriving a quantitative normalised assessment of the level within a group of criteria. To interpret the dependence of the initial estimates $\delta(l_g)$, the following membership functions built on the real experience of the participants of the tourist movement are considered [45]:

$$f_g(\delta_j(rp)) = \begin{cases} 0, & \delta_j(rp_g) < 0; \\ \left(\frac{\delta_j(rp_g)}{5}\right)^{\alpha}, & 0 \le \delta_j(rp_g) < 5;. \\ 1, & \delta_j(rp_g) \ge 5. \end{cases} \qquad (4)$$

$$f_g(\delta_j(rn)) = \begin{cases} 0, & \delta_j(rn_g) < 0; \\ \left(\frac{\delta_j(rn_g)}{5}\right)^{\beta}, & 0 \le \delta_j(rn_g) < 5;\ g = \overline{1,2}. \\ 1, & \delta_j(rn_g) \ge 5. \end{cases} \qquad (5)$$

Where α, β are thresholds that allow considering the expected and actual travel experience, considering positive and negative aspects. These thresholds are determined based on the analysis of the problems and psychological properties of the individual's behaviour. The output estimates of $f_g(\delta_j(rp)), f_g(\delta_j(rn))$ are derived based on actual travel satisfaction experience, considering the psychology of human reasoning, as expected corresponds to reality. The logic is as follows: a person gets more disappointment from traveling if the real experience does not meet expectations in positive aspects and vice versa, if in negative aspects the expected experience does not justify the real one. Therefore, considering the content of the initial assessment and applying real data for model verification, the following formal definition of thresholds α, β is proposed. For this, the membership rules are used, which formally represent a system of logical statements: "If, Then, Else" and connect the values of the input variables $\delta_j(ep_g), \delta_j(rp_g), \delta_j(en_g), \delta_j(rn_g), g = \overline{1,2}$, with one of the possible values of thresholds α, β respectively. Moreover, minor differences between the desired and actual are a stimulus to action, with significant ones having a negative effect. Differences in positive aspects result in a higher initial estimate; however, in negative aspects, they decrease. By conducting experiments on the real evaluation data of 2,343 experts, the rules of belonging were constructed and the values of the thresholds α, β were determined.

To derive a quantitative normalised estimate for the positive aspects of $f_g(\delta_j(rp)), g = \overline{1,2}$, the threshold α is determined as follows:

If $\delta(ep_g) = \delta(rp_g)$ Then $\alpha = 1$, Else …

If $\delta(ep_g) < \delta(rp_g)$ Then $\alpha = \frac{3}{5}$, Else …

If $\delta(ep_g) > \delta(rp_g)$ Then $\alpha = \frac{6}{5}$.

To derive a quantitative normalised estimate for negative aspects $f_g(\delta_j(rn)), g = \overline{1,2}$, the threshold β is determined as follows:

If $\delta(en_g) = \delta(rn_g)$ Then $\beta = 1$, Else ….

If $\delta(en_g) < \delta(rn_g)$ Then $\beta = \frac{8}{5}$, Else ….

If $\delta(en_g) > \delta(rn_g)$ Then $\beta = \frac{7}{5}$.

At the first stage, for the *j-th* expert, quantitative normalised level estimates are obtained for positive $f_1(\delta_j(rp)), f_2(\delta_j(rp))$ and negative aspects of $f_1(\delta_j(rn)), f_2(\delta_j(rn))$, according to criteria groups G_1 and G_2. Such a logical derivation for the evaluation criteria allows assessing the real satisfaction of the participants of the tourist movement, based on the psychology of the expected and real experience.

The second stage is aimed to derive the level of travel satisfaction relative to the expected and actual experience. Based on the obtained estimates, two aggregated quantitative estimates are constructed within the criteria group. To do this, the following function that changes the directionality of the target for negative aspects is proposed:

$$\begin{cases} \mu_{1j} = \frac{1}{2} * \left(f_1(\delta_j(rp)) + \left(1 - f_1\left(\delta_j(rn)\right)\right)\right) \\ \mu_{2j} = \frac{1}{2} * \left(f_2\left(\delta_j(rp)\right) + \left(1 - f_2\left(\delta_j(rn)\right)\right)\right) \end{cases}. \tag{6}$$

The change in goal orientation for negative aspects is explained by the fact that the greater the number of negative experiences, the lower the satisfaction with the trip. Therefore, if the scores $f_1(\delta_j(rn)), f_2(\delta_j(rn))$ tend to be 0, then this implies that the satisfaction is better. For a positive experience, on the contrary, the maximum satisfaction should go to 1. Therefore, the direction of the goal changes for a possible comparison.

It is proposed to apply knowledge intelligence and use multidimensional membership functions [45] to obtain a single aggregated estimate of the level of travel satisfaction relative to the expected and actual experience. For the aggregation of values μ_{1j}, μ_{2j} based on the conducted experiments, it is proposed to use the modeling of uncertainties of the "average value" type in the two-dimensional space of estimates [0; 1], using a cone-shaped membership function. The choice of the membership function is due to the fact that if both arguments go to 1, then the result will also go to 1. The value of the center of the base of the cone will be the unit vector $(x_1^0; x_2^0) = (1; 1)$, and the scaling according to the coordinates $(2; 2)$ will still be set. Then, the two-dimensional conical membership function will have the following form (Gavurova *et al.,* 2023):

$$\varphi_j = \begin{cases} 1 - \frac{1}{2} \cdot \sqrt{\left(\mu_{1j} - 1\right)^2 + \left(\mu_{2j} - 1\right)^2}, if\ \theta_j < 1 \\ 0, otherwise. \end{cases}, \qquad (7)$$

Where $\theta_j = \frac{1}{2} \cdot \sqrt{\left(\mu_{1j} - 1\right)^2 + \left(\mu_{2j} - 1\right)^2}$.

Thus, the initial aggregated estimates $\varphi_j; j = \overline{1, n}$ from the interval [0; 1], separately for *n* participants of the tourist movement, are formuloated. The level of travel satisfaction in relation to the expected and real experience, based on the information model of linguistic criteria for evaluating the level of tourist movement in relation to the infrastructure and accessibility of the tourist movement, is determined.

However, it is necessary to solve the problem of deriving one generalised value based on the values of aggregated estimates φ_j ($j = \overline{1, n}$) of experts in the researched region R_C. It is suggested to use convolution when the weights of experts are equally important:

$$m_{RC} = \frac{1}{n} \sum_{j=1}^{n} \left(\varphi_j\right)_{RC}. \qquad (8)$$

Where n is the number of participants in the tourist movement (experts), RC is the estimated region of the country C. The generalised score $m_{RC} \in [0; 1]$ characterises the generalised level of tourist movement in the region, assessed by the real experience of the participants in the tourist movement, in relation to infrastructure and accessibility.

To determine the linguistic level γ of tourist movement, relative to infrastructure and accessibility, the value obtained by formula (8) is mapped to one of the term-set variables $LT = \{lt_1, lt_2, \dots, lt_5\}$ according to the following evaluation content:1) $m_{RC} \in$ (0.8; 1] – lt_1 = "high level of tourist movement in relation to infrastructure and accessibility. This refers to the highest level of positive aspects of infrastructure and external and internal accessibility in the destination. The expected and actual experiences match, or the actual positive experience outweighs the expected one.

2) $m_{RC} \in$ (0.6; 0.8] – lt_2 = "above average level of tourist movement in relation to infrastructure and accessibility". This refers to the high level of positive aspects of infrastructure, external and internal accessibility in the destination. Expected and actual experiences match, or there is a slight advantage of the expected negative experience over the actual negative one.

3) $m_{RC} \in$ (0.4; 0.6] – lt_3 = "average level of tourist movement in relation to infrastructure and accessibility". This refers to the average level of positive aspects of infrastructure and external and internal accessibility in the destination. Expected and actual experience do not match. This might possibly be a situation where the expected

positive experience has a slight advantage over the actual one. A change in the situation is possible due to economic changes, both for the better and for the worse.

4) $m_{RC} \in (0.2; 0.4]$ – lt_4 = "low level of tourist movement in relation to infrastructure and accessibility". There are almost no positive aspects. Expected and actual experience do not match. Significant advantage of actual negative experience over expected is observed.

5) $m_{RC} \in [0; 0.2]$ – lt_5 = "very low level of tourist movement in relation to infrastructure and accessibility". A fundamental change in the situation regarding infrastructure investment, as well as a priori and empirical knowledge of industry subjects, is needed for its development in the region.

If for DM it is necessary to determine the level of tourist movement within country C, then formula (9) can be applied, or a convolutional approach with or without the introduction of weighting factors for regions. Similarly, the linguistic level of tourist movement within the country is determined.

3. Results

The results of the study were verified and tested on real data obtained from 2,343 participants of the tourist movement in the countries of the Visegrad Group: the Czech Republic, Hungary, Poland, and Slovakia. The data was collected from March to December 2021 from the respondents who participated in the tourism movement. They had to complete a research questionnaire, which is aimed at studying attitudes towards selected areas related to tourism. The selected respondents cover the full set of elements in the research problem and satisfy the quality assessments put forth regarding the formation of the data sample. The research questionnaire was created as part of the cooperation of several organisations. In total, the research questionnaire contained 132 questions, which were divided into 16 groups: information about the respondent; information about recreation; the quality of services provided at the accommodation facility; environment, nature, and weather; culture, local customs and traditions; food and beverages; sports and leisure; procurement and business services; infrastructure and external accessibility; infrastructure and internal accessibility; pricing; the attitude of residents and guests towards other guests (tourists); security; destination image; persecution, nagging at the destination; barrier-free; and costs. For example, input data for some expert after a trip in 2020, Liberec Region of the Czech Republic, is presented in *Table 2*.

Table 2. Input Expert Data from the Liberec Region

Name criterion	Positive aspects		Negative aspects	
	Expected experience (ep)	Real experience (rp)	Expected experience (en)	Real experience (ep)
G_1 – infrastructure and external accessibility				
K_{11}	Expected	Experienced	Unexpected	Haven't experienced
K_{12}	Expected	Experienced	Unexpected	Haven't experienced

Table 2 *(continuation)*. Input Expert Data from the Liberec Region

K_{13}	Expected	Experienced	Unexpected	Haven't experienced
K_{14}	Unexpected	Haven't experienced	Expected	Experienced
K_{15}	Expected	Experienced	Unexpected	Haven't experienced
G_2 – infrastructure and internal accessibility				
K_{21}	Unexpected	Experienced	Unexpected	Haven't experienced
K_{22}	Unexpected	Experienced	Unexpected	Haven't experienced
K_{23}	Expected	Haven't experienced	Unexpected	Experienced
K_{24}	Unexpected	Experienced	Unexpected	Haven't experienced
K_{25}	Expected	Experienced	Unexpected	Haven't experienced

Source: created by the authors.

Based on the provided input data, a model of fuzzy logical inference of the level of travel satisfaction relative to the expected and actual experience from infrastructure and accessibility – M_{FLC} will be illustrated.

At the first stage, the resulting quantitative estimates are obtained for each group of evaluation criteria, using elements of fuzzy logic. For this, according to the characteristic function (2), the input data is converted into binary and the sum of the scored points relative to the criteria groups is calculated according to the formula (3). Also, a quantitative normalised assessment of the level within the criteria groups according to formulas (4)–(5) is derived. The calculated results are given in *Table 3*.

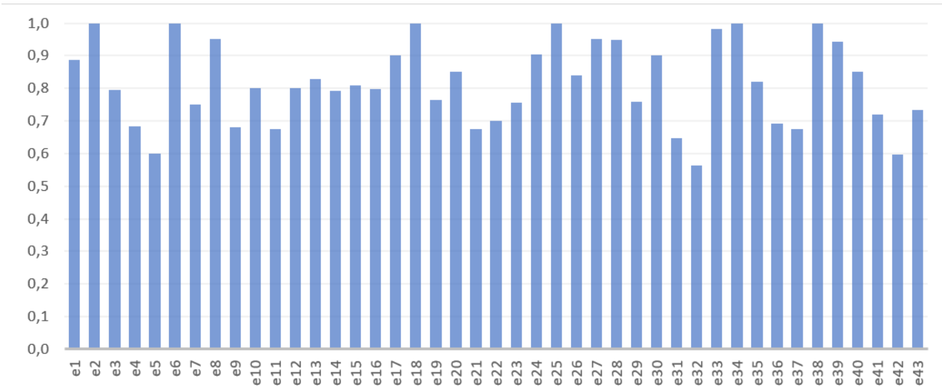
Table 3. Derivation of a Quantitative Normalised Assessment of the Level within Groups of Criteria

Source: created by the authors.

According to the groups of criteria G_1 and G_2 quantitative normalised level estimates for positive and negative aspects are obtained for a certain expert: $f_1(\delta(rp)) = 0.8$; $f_2(\delta(rp)) = 0.875$; $f_1(\delta(rn)) = 0.2$; $f_2(\delta(rn)) = 0.076$.

Based on the obtained estimates, two aggregated quantitative estimates are constructed within the criteria group according to the formula (6): $\begin{cases} \mu_1 = \frac{1}{2} * \big(0.8 + (1 - 0.2)\big) = 0.8; \\ \mu_2 = \frac{1}{2} * \big(0.875 + (1 - 0.076)\big) = 0.899. \end{cases}$

After that, a formula is used to obtain a single aggregated travel satisfaction score relative to the expected and actual experience (7): $\varphi = 1 - \frac{1}{2} \cdot \sqrt{(0.8 - 1)^2 + (0.899 - 1)^2} = 0.888$. As a result, an initial aggregated estimate of $\varphi = 0.888$ was obtained, which determines the level of travel satisfaction relative to the expected and real experience, based on the information model of linguistic criteria for evaluating the level of tourist movement in relation to the infrastructure and accessibility of tourist movement.



Source: created by the authors.

Figure 2. **Histogram of Aggregated Estimates of the Level of Tourist Movement for 2020 in the Liberec Region, the Czech Republic**

The problem was solved by deriving one generalised value of φ, which were participants of the tourist movement in 2020 in the following studied regions of the V4 countries: the Czech Republic, 43 experts in the Liberec Region; Slovakia, 54 experts in the Košice Region; Poland, 29 experts in the Pomeranian Voivodeship; Hungary, 29 experts in the Veszprém County. For example, input data of aggregated estimates of the level of tourist movement for 2020 in the Liberec Region, the Czech Republic, can be observed in *Figure 2*.

The generalised level of tourist movement in the regions of the V4 countries, assessed by the real experience of the participants of the tourist movement, in terms of infrastructure and accessibility, according to formula (8) is analysed next, respectively for the Czech Republic, Slovakia, Poland, Hungary: $m_{RC(CZ)} = 0.814$; $m_{RC(SK)} = 0.812$; $m_{RC(PL)} = 0.783$; $m_{RC(HU)} = 0.856$. To determine the linguistic level γ of tourist movement, the value is mapped to one of the variable term-sets LT. The results reveal that the Czech Republic, Slovakia, Hungary have $\{m_{RC(CZ)}, m_{RC(SK)}, m_{RC(HU)}\} \in (0.8; 1] - lt_1$ = “high level of tourist movement in relation to infrastructure and accessibility”, and Poland $m_{RC(PL)} \in (0.6; 0.8] - lt_2$ = “above average level of tourist movement in relation to infrastructure and accessibility” for 2020 in the selected regions.

4. Discussion

In the present study, a fuzzy model for evaluating the level of tourist movement to infrastructure and accessibility in the regions of the V4 countries is built. The model is based on travel satisfaction in relation to the expected and real experience of participants in the tourist movement in the evaluated region. The advantages of the fuzzy model derive from the mathematical model being based on input expert data of direct participants in the tourist movement of the studied region, sets and groups of linguistic criteria of the information model being open, the model not depending on their number, and system analysts having the possibility to always expand the set of criteria depending on available expert assessments. Also, the model makes it possible to understand the content of the studied region through the prism of the level of travel satisfaction relative to the expected and real experience from infrastructure and accessibility, in the space of evaluations. In addition, the fuzzy model reveals the uncertainty of input expert evaluations with the help of a fuzzy logical conclusion regarding the logic of the psychological properties of an individual's behaviour by introducing thresholds α, β which are verified on real data. All model settings are verified on real data, and the model focuses on an unbiased assessment of regions, which contains the content of informed management decision-making regarding the feasibility of improving accessibility and internal and external infrastructure in places of tourist movement. The disadvantages of this approach include the use of different types of membership functions, characteristic functions, and convolutions, which can lead to ambiguity in the final results.

The rationality of the obtained initial estimate $Y(f)$ for making management decisions proves the advantages of the developed model. The reliability of the obtained results is confirmed by the results of research, verification of the model on real data and is ensured by the justified use of the apparatus of fuzzy sets, fuzzy logic, and intellectual analysis of knowledge.

Conclusions

The global tourism industry has experienced a significant growth until the onset of the year 2020 due to the technological progress and the globalisation processes. The development of the tourism sector by the year 2040 will be influenced by the following megatrends: the development of visitor demand, the growth of sustainable tourism, technological development, and travel mobility. The infrastructure of the tourism sector is also related to these megatrends and is examined in many sectoral dimensions. It is assumed that the growth of the tourism sector will continue after the pandemic crisis and will be intensively influenced by the demographic changes, the environmental conditions, and the innovation processes. It will make demand forecasting processes more difficult and thus, it will create a pressure on the constant development of the methodological platform and the improvement of the decision-making mechanisms.

The main goal of the research was to develop a fuzzy model for evaluating the level of tourist movement to infrastructure and accessibility in the regions of the V4 countries. An information model of criteria for evaluating the level of tourist movement in relation to infrastructure and accessibility was developed for the first time. The set of criteria is open, and the model does not depend on their number. Criterion values are expert judgments about the positive and negative aspects of the infrastructure and external accessibility at the destination, relative to the expected and actual experience. System analytics can always add other important indicators.

For the first time, a model of fuzzy logical inference of level of travel satisfaction relative to expected and actual experience from infrastructure and accessibility is developed. The mathematical model is based on the application of intellectual analysis of knowledge and the logical conclusion of the level, considering the psychological properties of human behaviour, when the expected does not correspond to reality. Adherence rules have been built for the derivation of a quantitative normalised assessment of positive and negative aspects. The values of the thresholds α, β of positive and negative aspects were experimentally established, which allow taking into account the expected and real travel experience.

The research results were tested, and the developed model was verified on real data obtained from 2,343 participants of the tourist movement in the period 2017–2021 for the regions of the V4 countries. Examples of evaluation on fragments of data from different regions and for different periods are given. Simultaneously, the adequacy of the vague model for evaluating the level of tourist movement in relation to infrastructure and accessibility, developed in the work, was experimentally confirmed. The obtained results demonstrate the scientific and applied value of the conducted research, while absolutely proving its scientific hypothesis.

Demand forecasting will always be an important part of the decision-making mechanisms and its results will be essential for policymakers, the regional and national strategic plans, as well as the political analysts. The high-quality decision-making mechanisms in the field of tourism will not only support the development of tourism on a national and international level, but they will also enable the construction of the effective policies for the elimination of the regional disparities and discrepancies, which the differences in the economic and social development of the countries. In the post-COVID era, the economies of these countries must evolve beyond the conventional approaches to tourism development. It is imperative that they explore new, non-traditional forms of tourism that can support their economic growth and facilitate the sustainable development of this sector. Knowledge of potential demand will be the baseline for the identification of the new opportunities for tourism development, as well as for the strategic decisions at the level of the government, regional governing bodies, or the other territorial structures. The strong heterogeneity of the tourism sector associated with a wide range of the economic as well as non-economic factors affecting it will require continuous, systematic, and expansive development of the methodological processes and the construction of new and modified traditional methods. The analytical support, which can generate the most accurate results and ensure the highest quality decision-making processes, will always be the essential point for the sustainability of tourism and will ensure its competitiveness at the national, international, and global level.

The results represent the valuable outputs for policymakers at national as well as international levels and for international research teams to establish international research cooperation networks. They will also support the development of the international benchmarking indicators, which would enable the comparison of the comparable segments, and simultaneously reveal the driving forces of the development of sustainable tourism. The need to build international databases is also related to these consistent facts.

The present study was limited by the sample of respondents of the research questionnaire, as well as the use of different types of membership functions, characteristic functions, and convolutions. Such a limitation may lead to ambiguity in the results. Further research of the problem is possible in the developed vague hybrid models: the evaluation of the level of tourist movement of the V4 regions in relation to culture, traditions and food; decision-making support for financing the development of tourism in the V4 countries; evaluation of the level of satisfaction with the tour taking into account different social classes of experts, duration of trips, the amount of money spent on the trip and other indicators.

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NEAPIBRĖŽTAS MODELIS REGIONINIAM TURIZMUI IR PRIEINAMUMUI VERTINTI

Beata Gavurova, Volodymyr Polishchuk, Inna Polishchuk

Santrauka. Paklausos prognozavimas ir jos dimensijos, taip pat ir turizmo infrastruktūra dar nėra pakankamai išnagrinėti. Remiantis atliktais tyrimais galima daryti išvadą, kad paklausos tyrimams taikomos tradicinės turizmo paklausos teorijos ir įvairūs modeliniai metodai. Dėl šios priežasties atsiveria pakankamai galimybių tobulinti techniką, metodus, būdus ir priemones, leidžiančius gauti naujus rezultatus, sprendimus, kurie padėtų formuluoti priėmimo procesus ir politiką. Šio tyrimo tikslas – sukurti neapibrėžtą modelį, skirtą įvertinti turistų judėjimą į infrastruktūrą ir prieinamumą V4 šalių regionuose. Remiamasi kelionės pasitenkinimu, jis lyginamas su turistų lūkesčiais ir jų realia patirtimi. Pirmą kartą sukurtas neapibrėžtos logikos išvados modelis, skirtas vertinti kelionių pasitenkinimo lygį, jį palyginti su tikėtina ir realia patirtimi, susijusia su turizmo infrastruktūra ir prieinamumu. Tyrimo rezultatai buvo išbandyti, o sukurtas modelis patikrintas remiantis realiais duomenimis, gautais iš 2 343 turistų, keliavusių po V4 šalių regionus. Efektyvi politika ir veiksmingi sprendimų priėmimo procesai yra vieni svarbiausių būdų, galinčių padėti pašalinti regioninius skirtumus ir neatitikimus, veikiančius kiekvienos šalies ekonomiką, sveikatos apsaugą, socialinę sritį ir aplinką.

Reikšminiai žodžiai: sprendimų priėmimas; hibridinis modelis; ekspertų žinios; neapibrėžtos aibės; neapibrėžtos logikos išvados; turizmas; turizmo infrastruktūra.