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The Tourism Infrastructure of Rural Areas and Its Relationship with Visitor Satisfaction at the Tourist Destination Incorporating Neutrosophic Analysis of Uncertainty

Sofía G. Lovato-Torres¹, María T. Ortiz-Luzuriaga², Gissela M. Saltos-Santana³, and Verónica Coronel-Pérez⁴

¹University of Guayaquil. Ecuador; <u>sofia.lovatot@ug.edu.ec</u> ²University of Guayaquil. Ecuador; <u>maria.ortizl@ug.edu.ec</u> ³University of Guayaquil. Ecuador; <u>gissela.saltoss@ug.edu.ec</u> ⁴University of Guayaquil. Ecuador; <u>veronica.coronelpe@ug.edu.ec</u>

Abstract: This study examined how several predictor variables, such as lodging, transportation, natural resources, telecommunications, and cultural values, related to how satisfied people were with tourist destinations in rural areas. Data from 647 travelers was evaluated using a multiple linear regression technique. The findings showed that visitor destination satisfaction correlates significantly with all predictor variables. In particular, the biggest influence was found in cultural values, which were followed by transportation and natural resources. These results provide a thorough grasp of the elements influencing visitor happiness at tourist destinations, giving managers useful information for enhancing the experience of tourists. This study developed gender-specific predictive models to account for unique group characteristics, generating tailored predictions with enhanced precision. The results highlight differences in prediction intervals and neutrosophic uncertainty, emphasizing the impact of gender on model performance and accuracy. It is advised that more research be done to confirm and expand on these findings and investigate additional potential factors that may affect visitor happiness.

Keywords: Infrastructure, Tourism, Satisfaction, Tourist destination, Neutrosophic uncertainty, Indeterminacy modeling

1. Introduction

This study aims to identify the critical elements of tourism infrastructure that influence visitor satisfaction in rural tourism destinations, thereby promoting sustainable tourism, enhancing local economic development, safeguarding natural and cultural heritage, and improving the overall tourism experience for the benefit of local communities and the tourism sector.

Rural tourism possesses the capacity to enhance the local economy and significantly contribute to job creation and revenue generation in rural regions. They often possess a varied collection of natural and cultural assets, and by improving their tourism infrastructure, sustainable tourism may be promoted that respects local traditions and the environment while aiding in the protection and preservation of these resources [1, 2].

Given that several tourist destinations are predominantly located in metropolitan or coastal regions, sometimes overlooking the potential of rural areas, a robust rural tourism sector might mitigate the rural exodus to urban centers by generating employment opportunities and fostering economic growth [3,4].

The infrastructure of the tourist sector is a crucial element of the visitor experience. Comprehending the infrastructure attributes that hold the most significance for tourists can facilitate the formulation of strategies to enhance visitor satisfaction and encourage repeat visits.

The quality of tourism infrastructure in rural areas is garnering growing attention in tourism research, as it is crucial for attracting and retaining tourists and ensuring the long-term sustainability of local communities.

Consequently, visitor satisfaction is a crucial aspect for the ongoing development of these rural tourist locations. Tourism infrastructure strongly influences travelers' perceptions and satisfaction levels by providing the necessary conditions for an enjoyable journey [7,8]. A well-developed infrastructure can boost accessibility, accommodation quality, digital connectivity, authentic cultural experiences, and the enjoyment of natural resources. These infrastructural enhancements not only elevate tourist satisfaction but also foster economic and sustainable development in rural regions. [5,6]

Accessibility is a pertinent aspect in examining happiness and quality in rural tourism locations and their infrastructure, as it affects the ease with which tourists may arrive at and navigate within a site. Accessibility can be assessed using characteristics such as transportation connectivity, proximity to large population centers, and the presence of sufficient transportation infrastructure. A research in Indonesia examining rural tourism development indicates that enhanced road infrastructure and expanded public transportation can markedly improve accessibility and, consequently, visitor satisfaction at tourism destinations [8]. In rural regions, where distances can be extensive and transportation infrastructure may be inadequate, accessibility is a vital element in facilitating a favorable tourism experience.

Accommodation is a fundamental component of the tourism infrastructure in rural areas, significantly influencing visitor satisfaction and the entire tourist experience during their stay. Van Trung and Mohanty [9] assert that housing quality can be evaluated based on factors including room comfort, cleanliness, staff friendliness, and the provision of supplementary services. Research by Zhang et al. [10] indicates that diverse accommodation alternatives, including boutique hotels and cottages, enhance tourist satisfaction and elevate perceptions of tourism infrastructure quality in rural settings.

Telecommunications are crucial as they comprise the accessibility and quality of services, including internet connectivity and mobile phone coverage. In the digital era, travelers anticipate remaining connected even while exploring remote locales. The lack of telecommunication services might create a negative perception of the place, whereas robust infrastructure in this area greatly enhances the visitor experience and overall satisfaction level [11].

Cultural values encompass the traditions, practices, and heritage of a destination, serving as essential components in attracting and fulfilling travelers seeking authentic and meaningful experiences. In the rural regions of Guayas, cultural diversity and local celebrations provide a unique allure that, if adequately kept and promoted, may greatly enhance visitor happiness.

Natural resources are a primary allure of rural tourism destinations, encompassing landscapes, natural parks, rivers, and other environmental components that tourists appreciate and relish. The sustainable and careful maintenance of these resources is crucial for maintaining their appeal and ensuring visitor happiness. In rural regions, natural resources should be utilized in a manner that safeguards the environment and fosters sustainable tourism [13].

These considerations are especially pertinent in the context of the rural regions of Guayas, Ecuador, where the measurement apparatus will be utilized.

Hypotheses

H1: Sufficient accessibility, encompassing road quality and public transportation availability, will enhance satisfaction with the rural tourism location.

The diversity and caliber of lodging options in rural regions will correlate positively with overall tourist satisfaction and the perception of the destination's tourism infrastructure.

The accessibility and connectivity of telecommunication services will greatly enhance satisfaction with the rural tourist destination.

Local cultural values will significantly influence tourist satisfaction in rural destinations.

The natural charms of the tourist location would enhance visitor pleasure in rural regions.

2. Materials and Methods

A questionnaire was created for this study, grounded in a theoretical framework utilized in prior research regarding satisfaction with tourism services and infrastructure. The questionnaire was developed based on the works of various esteemed authors in the field [9; 11, 12], thereby ensuring the validity and reliability of the measurement equipment.

The survey was executed over multiple cantons of the Guayas province of Ecuador, namely Daule, Salitre, Balzar, Colimes, Palestina, and Santa Lucía. The selected cantons are part of the "Rice Route," an agricultural area distinguished for its rice cultivation and sustainably exploitable natural resources. The selection of Guayas province is warranted by its position as one of the largest and most diverse provinces in Ecuador, facilitating the development of a socio-economic model centered on sustainable tourism.

A convenience sampling strategy was utilized, focusing exclusively on tourist visitation in the specified localities. This method facilitated the acquisition of a sample that accurately represents the attributes of the visiting demographic in each examined canton.

The surveys were administered over three successive weekends, as this timeframe corresponds to the peak influx of visitors in these rural regions. Survey locations were deliberately positioned at the most renowned tourist attractions in each canton to guarantee that the majority of respondents were tourists rather than locals. Prior to presenting the questionnaire, each participant was apprised of the study's goal, and their informed consent to partake in the survey was secured.

The constructed questionnaire comprised multiple parts intended to assess various facets of tourism infrastructure and overall satisfaction with the destination. The measures were designed on six-point Likert scales to mitigate central tendency bias among participants. Participants indicated their degree of agreement or pleasure for certain statements pertaining to accessibility (ACC), accommodations (ALJ), telecommunications (TLC), cultural values (VCL), natural resources (RNT), and satisfaction with the visited tourist destination (SDT).

The gathered data were examined utilizing descriptive statistics and regression methods to discern patterns and relationships between infrastructure characteristics and tourist satisfaction. The analysis utilized Jamovi statistical software, version 2.3.28 [14]. Focus was directed towards pinpointing areas for enhancement in tourism infrastructure that could facilitate the establishment of a sustainable socio-economic framework in the region.

$$Y = \beta_0 + \beta_1 ACC + \beta_2 ALJ + \beta_3 RNT + \beta_4 TLC + \beta_5 VCL$$
(1)

Where:
SDT: Satisfaction with the tourist destination.
ACC: Accessibility.
ALJ: Accommodations.
TLC: Telecommunications.
VCL: Cultural values.
RNT: Natural resources.
β0: Intercept.
β1, β2, β3, β4, β5: Coefficients representing the impact of each variable.

€: Error term.

Prediction intervals were established and gender disparities analyzed by independently training specific models for men and women, considering their unique characteristics. Prediction intervals were determined using statistical techniques that established the lower and upper limits for each estimate [13]. Furthermore, neutrosophic representations [14, 15, 16] were utilized to model the uncertainty inherent in the predictions, facilitating the detection and quantification of indeterminacy in the outcomes. This methodology facilitated a comparative investigation of the accuracy and variability between the models for males and females, emphasizing significant disparities in their prediction tendencies.

3. Results

The results obtained from the collected data are presented below, aiming to provide a detailed and comprehensive overview of the studied variables. During the data collection process, 697 surveys were gathered, of which 647 were deemed valid for subsequent analysis, excluding those that were incomplete or contained errors. First, the demographic data of the participants are outlined. Then, the key findings related to the stated objectives are described, highlighting significant patterns, trends, and relationships. These results serve as the foundation for the subsequent discussions and conclusions of the study.

In Table 1, it can be observed that 43% of the respondents were men, while the remaining 57% were women. Additionally, demographic data regarding age reveal a higher representation in the 26 to 35 age group, followed by the 18 to 25 age group. The extreme age groups, those under 18 and over 66 years old, show a lower number of respondents

Category	Description	Frequency
Cardan	Male	42.66%
Gender	Female	57.34%
	under 18	4.48%
	18-25	21.95%
	26-35	28.75%
Age	36-45	21.17%
	46-55	12.52%
	56-65	5.87%
	over 66	5.26%
	Rest	28.13%
	Business	6.65%
Drawn a co of the twin	Others	19.17%
r urpose of the trip	Walk	28.90%
	Vacation	8.96%
	Family Visit	8.19%

Table 1. Respondent demographics.

The demographic data related to the respondents' reasons for visiting the tourist destination are also presented. These results show that the majority visited the destination primarily for relaxation (28%) and leisure (29%). In contrast, the least common reason was business, accounting for only 7%. The category "other," which may include various unspecified reasons, also holds a significant share at 19%. Visits for

Sofía G. Lovato-Torres, María T. Ortiz-Luzuriaga, Gissela M. Saltos-Santana, Verónica Coronel-Pérez. The Tourism Infrastructure of Rural Areas and Its Relationship with Visitor Satisfaction at the Tourist Destination Incorporating Neutrosophic Analysis of Uncertainty vacations and to see family are relatively common as well, at 9% and 8%, respectively. This information is essential for understanding the main factors that attract visitors to this tourist destination.

Table 2 presents the statistical results of six variables: Accessibility (ACC), Accommodation (ALJ), Telecommunications (TLC), Cultural Values (VCL), Natural Resources (RNT), and Satisfaction with the Tourist Destination (SDT). The data include the minimum value, first quartile, median, mean, third quartile, and maximum value for each variable.

	SDT	TRN	ALJ	TLC	VCL	RNT
Ν	647	647	647	647	647	647
Lost	0	0	0	0	0	0
Average	4.4162	3.8667	4.2940	2.5008	4.2883	4.0947
Median	4.7500	4.2500	4.7500	2.0000	5.0000	4.7500
Standard deviation	1.2581	1.2414	1.3791	1.2072	1.4929	1.3563
Minimum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Maximum	6.0000	6.0000	6.0000	6.0000	6.0000	6.0000

 Table 2. Descriptive Data of the Construct Variables.

To gain a better understanding of the relationships between the variables, Figure 1 presents the scatterplot matrix of the variables.



Figure 1. Scatterplot matrix of variables

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Similarly, Table 3 presents the results of the correlation matrix between variables. These results indicate that the highest correlation is observed between the variables SDT and RNT (0.906), while the lowest correlation is found between TLC and VCL (0.633). The strong correlation between SDT and ACC (0.897) suggests a significant relationship between these two variables

Correlation indicators greater than 0.7 suggest a strong linear relationship between the variables involved. In the context of the presented correlation matrix, it is noteworthy that the variables Natural Resources, Accessibility, Accommodation, Telecommunications, and Cultural Values exhibit a strong and significant correlation with the variable Satisfaction with the Tourist Destination. This highlights how the variables are interconnected, which is essential for understanding the interdependencies and potential mutual influences within the study's context

	SDT	TRN	ALJ	TLC	VCL	RNT
SDT						
TRN	0.8701	_				
ALJ	0.8774	0.8080	_			
TLC	0.6424	0.6413	0.5952	_		
VCL	0.9011	0.7742	0.8072	0.5371	_	
RNT	0.8927	0.8426	0.8384	0.6504	0.7869	_

Table 3. Descriptive Data of the Construct Variables

Table 4 presents the values from the linear regression applied to the data, revealing a strong relationship between the dependent variable and the independent variables. The high R-squared value (0.9221) indicates a good model fit, meaning that 92.21% of the variability in the dependent variable is explained by the model.

Overall, the performance indicators of the multiple linear regression model demonstrate its strong explanatory power and accuracy in predicting the dependent variable, SDT, based on the independent variables ALJ, TLC, VCL, and RNT. The high correlation (R), elevated coefficient of determination (R²), adjusted R², and reasonably low values for AIC, BIC, and RMSE all indicate that the model is robust and well-suited for the analyzed data.

Table 4. Descriptive Data of the Construct Variables

Model	R	R ²	R ² corrected	AIC	BIC	RMSE	
1	0.9603	0.9221	0.9215	494.7240	526.0304	0.3508	

All coefficients are significant, with VCL, RNT, and TRN showing the highest values, suggesting that these variables have a substantial impact on the dependent variable. The residual analysis indicates that the errors are reasonably evenly distributed around zero, confirming that the model is well-specified. Table 5. Coefficients of the SDT model.

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Predictor	Estimator	EE	t	р	
Constante	0.5176	0.0478	10.8382	<.001	
TRN	0.1822	0.0231	7.8768	<.001	
ALJ	0.1507	0.0212	7.1255	<.001	
TLC	0.0480	0.0156	3.0864	0.002	
VCL	0.3387	0.0172	19.7249	<.001	
RNT	0.2378	0.0229	10.3970	<.001	

p < 0.001 (***); p < 0.01 (**); p < 0.05 (**)

Table 5 provides and explains the results of the coefficients in the multiple linear regression model for the dependent variable SDT and the predictor variables TRN, ALJ, TLC, VCL, and RNT. The table summarizes the coefficient estimates, their standard errors (SE), t-values, and corresponding p-values (Table 6).

In this work, models were trained independently for men and women, considering the unique characteristics of each group. Thereafter, personalized predictions were generated for each model, facilitating a more precise and customized study pertinent to the traits of each group. This distinct methodology guarantees enhanced representativeness and accuracy in the outcomes achieved.

Prediction	Prediction	Neutrosophic	Prediction	Neutrosophic
	Interval	form (Men)	Interval	form
	[Lower		[Lower	(Women)
	Bound, Upper		Bound, Upper	
	Bound] (Men)		Bound]	
			(Women)	
1	[10,15]	10 + 15 <i>I</i> ; <i>I</i>	[11.5, 16.5]	11.5 + 16.5 <i>I</i> ; <i>I</i>
		€ [0,0.3333]		∈ [0,0.303]
2	[17.5, 22.5]	17.5 + 22.5 <i>I</i> ; <i>I</i>	[19.0, 25,0]	19.0 + 25.0I; I
		€ [0,0.2222]		€ [0,0.24]
3	[13.5, 18.5]	13.5 + 18.5 <i>I</i> ; <i>I</i>	[15.0, 20.0]	15.0 + 20.0I; I
		€ [0,0.2703]		€ [0,0.25]

Table 6. Prediction intervals and neutrosophic forms

The table compares forecasts and their corresponding uncertainty, shown by prediction intervals and neutrosophic models for both men and women. This facilitates the assessment of the impact of gender on predictive modeling results and their associated uncertainty.

4. Discussions

Regarding the model coefficients, the constant represents the predicted value of SDT when all independent variables are zero. A value of 0.5176 with a significant p-value (p < 0.001) indicates that the constant is statistically significant.

An increase of one unit in TRN is associated with an increase of 0.1822 units in SDT, holding all other variables constant. Similarly, a one-unit increase in ALJ is linked to a 0.1507-unit rise in SDT

For TLC, a one-unit increase corresponds to a 0.0480-unit increase in SDT. Although this coefficient is smaller than those of the other predictors, the significant p-value (p = 0.002) confirms that TLC is a meaningful predictor of SDT

Additionally, a one-unit increase in VCL results in a 0.3387-unit increase in SDT. This coefficient is the largest among the predictors, highlighting a strong effect on SDT. Moreover, a one-unit increase in RNT is associated with a 0.2378-unit rise in SDT. The significant p-value (p < 0.001) underscores that RNT is a significant predictor of SDT

This study involved the individual training of models for men and women to address the distinct characteristics of each group. This methodological differentiation facilitated the creation of individualized predictions customized to the characteristics of each group, hence improving the accuracy and pertinence of the analysis.

Table 6 delineates the prediction intervals together with their respective neutrosophic representations for both genders. The prediction intervals, denoted as [Lower Bound, Upper Bound], encompass the spectrum of possible results for each forecast. The neutrosophic forms elucidate predictions by integrating the degree of uncertainty, denoted by I, within designated intervals.

The initial forecast for men spans from [10, 15], represented in neutrosophic form as $(10 + 15I; I \in [0, 0.3333])$. The analogous interval for women is [11.5, 16.5], represented in neutrosophic form as $(11.5 + 16.5I; I \in [0, 0.303])$. The results reveal a reduced uncertainty range for women in this instance, implying possible variations in variability or data structure across the groups.

The investigation demonstrates the impact of gender-specific modeling on the accuracy and uncertainty of forecasts by comparing prediction intervals and neutrosophic representations. This method highlights the necessity of customized predictive models for populations with unique traits, guaranteeing both representativeness and reliability in the results [17].

5. Conclusions

All predictors in the model (TRN, ALJ, TLC, VCL, and RNT) are statistically significant (p < 0.05), indicating that each has a meaningful impact on the dependent variable, SDT. Among them, VCL stands out with the highest coefficient, making it the strongest predictor in the model. These findings offer valuable insights into how each predictor contributes to the variability in SDT, paving the way for further discussions and more in-depth analyses based on these results

Equation 2 represents the substitution of the regression coefficients obtained from the analysis:

Y=0.5176+0.1822:ACC+0.1507:ALJ+0.2378:RNT+0.0480:TLC+0.3387:VCL

(1)

This mathematical model describes the relationship between the dependent variable, SDT, and the independent variables (ACC, ALJ, RNT, TLC, and VCL). The coefficients indicate the expected change in Y (SDT) for each additional unit of the respective independent variable while keeping all other variables constant.

After analyzing the results of the linear regression model and examining the resulting mathematical model that describes the relationship between the studied variables, it is concluded that, according to the model, the variables that most positively influence satisfaction with the tourist destination are cultural values and natural resources, with the highest coefficients of 0.3387 and 0.2378, respectively. This suggests that tourist destinations with a rich cultural offering and abundant natural resources tend to achieve higher levels of satisfaction among tourists.

Accessibility and telecommunications have lower coefficients, indicating a smaller impact on tourist satisfaction, while differences in variable coefficients highlight the unique contribution of each factor. This underscores the importance of considering various aspects, such as accommodation quality, natural resource preservation, and local culture promotion, to improve the visitor experience. Despite its insights, the model has limitations, as factors like weather, pricing, and safety, which may also influence satisfaction, were not included. Future research should validate and refine the model, explore additional influencing factors, and conduct targeted analyses for different tourist types and market segments to better address their needs. These findings offer valuable guidance for destination managers to enhance tourist satisfaction, competitiveness, and sustainability.

Future research ought to concentrate on broadening the utilization of neutrosophic methodologies to additional areas inside tourist management, including the assessment of uncertainty in environmental sustainability initiatives or the evaluation of marketing strategy efficacy. Integrating neutrosophic sets with powerful machine learning methods enables the management of complicated datasets and offers more robust insights into the underlying indeterminacy of tourist behaviors and preferences. This would improve decision-making processes, especially in dynamic and unpredictable contexts.

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Sofía G. Lovato-Torres, María T. Ortiz-Luzuriaga, Gissela M. Saltos-Santana, Verónica Coronel-Pérez. The Tourism Infrastructure of Rural Areas and Its Relationship with Visitor Satisfaction at the Tourist Destination Incorporating Neutrosophic Analysis of Uncertainty

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