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Determinants of Tourism Demand Using Machine Learning Techniques

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Abstract

The purpose of the current study was to determine factors affecting tourism demand using machine learning techniques. The results of different linear regression and random forest models on both the train and test sets were compared using RMSE and R^2. The random forest model outperformed the linear regression model on both the training and test sets. Climate, consumer price index, political stability, distance, promotion expenditure, and region of residence are all important factors in explaining total arrivals. The findings of the current research, therefore, provide additional evidence for the effectiveness of the AI based models to improve tourism demand forecasting compared to linear regression models.

Keywords: Tourism demand; random forest; feature importance

Introduction

Over past five decades, the tourism sector has been steadily growing over time and is among the main sectors contributing to economic growth and development (Peng et al., 2015**;** Martin et al., 2017). The tourism sector is among the main contributors to GDP, job creation, foreign exchange reserves and improvement in Balance of Payment (BOP) (Abedtalas, 2015; Habibi, 2017**;** Khoshnevis & Khanalizadeh, 2017). The tourism sector also plays a key role in export promotion, improving infrastructure, promoting cultural heritage and international cooperation. Moreover, the tourism sector contributes to economic development through its multiplier effects on other sectors in the value chain (Seetanah & Sannassee, 2015). It also contributes to the enhanced technology, foreign and investment attraction (Seetanah & Sannassee, 2015)

Researchers have increasingly shown interest in studies about international tourism demand (Kim et al., 1992). At macro level, tourism demand is determined by the level of GDP, exchange rate and relative prices (Martins et al., 2017). Tourism was found to be sensitive to the change in macroeconomic environment (Kim et al., 2018). Tourism demand also depends on the level of political stability and safety, infrastructure development and the level of destination promotional efforts (Seetanah & Sannassee, 2015). In addition, external shocks such as disasters and financial crisis have adverse effects on tourism demand (Muryani et al., 2021).

Methodological issues and variations in findings have made researchers deploy efforts to identify the sources of differences in tourism demand estimates and methodological issues in predicting tourism demand elasticities (Rosselló et al., 2005). The results of metadata analysis revealed that the variability of estimates in tourism demand modelling can be attributed to the estimation methods used, frequency of data, model specification, destination, time period covered and the sample size (Peng et al., 2015)

Though several attempts have been made to identify the determinants of tourism demand (Claveria et al., 2015; Huang & Hao, 2021; Kilimci et al., 2019; Law, 2000), the application of machine learning techniques to identify the determinants of tourism demand has been given little attention. Therefore, the current study compares the results of Radom forest and linear regression models using RMSE and R- squared to identify factors affecting tourism demand. The remainder of the paper is organized as follows: the next section focuses on the literature review. Section three describes data sources, model specifications and methods used for data analysis. Section four discusses the results and findings of the study. The last section focuses on the conclusions and proposed areas of future research.

Literature review

Analyzing factors affecting tourism demand plays a key role to understand current and future trends, and thus be able to better predict future tourism demand (Peng et al., 2015). Over the past five decades, a rampant and consistent growth of the tourism sector has attracted the interest of many researchers to model and predict the future demand behavior of tourists (Crouch,1994; Lim, 1997**;** Peng et al., 2014; Peng et al., 2015**;** Song & Li, 2008; Witt & Witt,1995; Dogru et al., 2017). A growing number of researchers have increasingly shown interest in studies about new developments in tourism demand modeling overtime (Khoshnevis& Khanalizade, 2017) and as a result, new theoretical and methodological developments have emerged. The variability of estimates in tourism demand modeling were found to widely vary in terms of model specification, period of time covered, data used, estimation method used, destinations and origins (Khoshnevi & Khanalizadeh, 2017).

Theoretical foundation

Tourism is defined as the consumption of goods and services by tourists at specific destination **(**Permatasari & Padilla, 2020). The uniqueness of tourism products results from the fact that it consists of interlinked goods (complex value chain) of which production and consumption occur concurrently (Rosselló et al., 2005). One common feature of tourism products and consumer goods is that both are not frequently consumed as it takes time for tourists to gather information about destinations, and as a result, tourists tend to limit their choices to the destinations they have enough information about (Vanegas et al., 2020).

The nature and attributes of the tourism product affect tourism demand elasticities in the following ways : (1) Tourists bear risks resulting from the purchase of international tourism that involves the buyer (tourist) and the seller from different destinations; (2) Destinations consist of a set of tourism products that include a wide range of attractions and experiences, which makes it hard for the buyers (tourists) to make a decision; (3) Tourism demand involves travel experience due to distance and costs involved from origin to destination.; (4) Exchange rate and product pricing are critical elements as tourists are obliged to make transactions in foreign currencies (Adeola et al., 2018).

Tourism demand is built on the theory of consumer demand (Peng et al., 2015; Adeola et al., 2018). The consumer (tourist) decision to travel or not to travel to a specific destination and cost-benefit analysis about alternative destinations reflect microeconomic theory. Tourism demand also reflects properties of the demand function such as homogeneity, symmetry and adding-up (Peng et al., 2015; Adeola et al., 2018), tourism demand is expressed as a function of tourist purchasing power (income), own prices and prices of alternative destinations, economic and non-economic factors, government regulations (Martins et al., 2017), demographic factors and social cultural factors (Khoshnevis & Khanalizadeh, 2017).

Development of research in tourism economics

Before the 1990s, researchers had paid little attention to tourism demand modelling. From 1995, however, new developments in tourism demand emerged. In 1995, Tourism Economics Journal was established and the International Association for Tourism Economics was created in 2007 (Dwyer et al., 2011)**.** Four major trends can be observed from the analysis of existing empirical findings in tourism economics. (1) Empirical studies in tourism economics have followed several avenues and the methodologies used tend to vary across different studies. Key research topics that arose include: tourism modelling and forecasting, economic impact of tourism and tourism industry analysis**;** (Stabler et al., 2009); (2) Several research areas of interest have arisen to test economic theories such as game theory, the economics of climate change and chaos theory. (3) There still exist grey research areas such as ecological economics and sustainable development, and poverty reduction, and this was due to methodological issues and sophistication involved in tourism demand modelling. (4) Tourism demand has been quantitative and as a result, the produced body of knowledge does not address existing real-world challenges in the tourism sector in a more holistic way given the complex nature of tourism products. Therefore, there is a need for new and diversified methods and methodologies to contribute to the theory development in tourism economics that has been so far overlooked (Dwyer et al., 2011)

Research about tourism demand modelling has recently followed new directions. This was motivated by the introduction of the hedonic pricing models, and discrete choice related studies (Chen, & Rothschild, 2010**;** Sinclair, 1998; Clewer et al., 1992; Papatheodorou, 2002). More recently, new developments emerged using panel data to evaluate different types of tourism markets (Naudé & Saayman, 2005; Van Der Merwe & Saayman, 2008). With the development of research in tourism economics, tourism demand modelling is increasingly becoming more complicated in terms of study-specific contexts, datasets used, model specification and model estimation techniques and more attempts are more likely to be made to refine econometric models and techniques to improve theoretical foundation and respond to the aspirations of researchers and decision-makers to better model and predict tourism demand (Dwyer et al., 2011)

Variability in tourism demand estimates and methodological approaches

In most of the empirical studies about international tourism demand, income elasticities were expected to have positive signs, while price elasticities of demand were supposed to have a negative signs. The deviation from the expected signs would be attributed to factors such as estimation errors, countries of origin and destinations and methodological issues (Crouch, 1992) Tourism demand elasticities were found to vary as a result of varied dummy variables used to capture different effects, the complexity involved in pricing tourism products given its nature, a mixture of prices and income measures used, origin countries and alternative destinations, methodological approaches (Crouch, 1992**;** Crouch, 1994). The extent of variation in tourism demand elasticities also depends on estimation methods used, data measurements, the sample size, and the period of time covered (Peng et al., 2015).

Determinants of tourism demand

Over past two decades, a growing number of researchers have attempted to predict tourism demand and the main determinants of tourism demand that were used in most the studies include income per capita, price in destination country (Consumer price index), relative prices, transport costs (Peng et al., 2015; Magableh & Kharabsheh, 2013; Adeola et al. , 2018; Dwyer et al., 2011; Kim et al., 2018; Vanegas et al., 2020; Kumar et al., 2019; Wu et al., 2017; Agyeiwaah & Adongo, 2016; Adeola et al., 2018); Price of substitute or alternative destinations and financial crisis (Agyeiwaah & Adongo, 2016; Kumar et al., 2020; Wu et al., 2017; Tang & Tan,2016); travel distance (Tatoglu & Gul, 2019; Permatasari & Padilla, 2020; Kumar et al., 2020; Tavares & Leitao, 2017) ; exchange rate (Martins et al., 2017; Permatasari & Padilla, 2020; Dwyer et al., 2011; Adeola et al., 2018 ; Vanegas et al., 2020; Kumar et al., 2020; Wu et al., 2017; Tavares & Leitao, 2017) ; population size (Peng et al., 2015; Agyeiwaah & Adongo, 2016; Martins et al., 2017; Tatoglu & Gul, 2019; Agyeiwaah & Adongo, 2016; Vanegas et al., 2020; Kumar et al., 2020; promotion expenditures (Peng et al., 2015; Adeola et al., 2018; Dwyer et al., 2011; Otero-Giráldez et al., 2012; Seetanah & Sannassee, 2015; Vanegas et al., 2020 ; Wu et al., 2017); climate (Peng et al., 2015 ; Adeola et al. , 2018; Otero-Giráldez et al., 2012; Kumar et al., 2020; Tavares & Leitao, 2017; political stability (Peng et al., 2015; Permatasari & Padilla , 2020; Dwyer et al., 2011; Vanegas et al., 2020; Tang & Tan, 2016 ; Tavares & Leitao, 2017); infrastructure (Magableh & Kharabsheh, 2013; Permatasari & Padilla , 2020; Adeola et al., 2018); One- off events (Peng et al., 2015; Dwyer et al., 2011; Kim et al., 2018 ; Tang & Tan , 2016) ; Taste and Preferences (Peng et al. , 2015; Agyeiwaah & Adongo, 2016 ; (Adeola et al. , 2018) ; Lagged Values of the Dependent and Independent Variables (Peng et al., 2014) ; Tatoglu& Gul, 2019; Adeola et al. , 2018; Kumar, 2020) ; visa-free entry (Tatoglu & Gul, 2019) .Other determinants of tourism demand that were not frequently used include Unemployment (Adeola et al., 2018); Level of accommodation (Permatasari & Padilla, 2020); Peng et al., 2015); Education level of the tourist (Peng et al., 2014). However, all these studies failed to provide new evidence for the application of machine learning techniques to identify factors affecting tourism demand.

Methodology

Data sources

The dataset used in the current study consist of 9348 monthly observations that were collected from various sources. The latter include national and international data sources as indicated in the table below:

Table 1. variables and data sources

Variable	**Data source**
Tourism arrivals by purpose and origin	Rwanda Development Board (RDB)
Consumer Price Index (CPI)	National Institute of Statistics of Rwanda (NISR)
Exchange rate	IMF database
Temperature	Rwanda Meteorology Agency
Precipitation	Rwanda Meteorology Agency
Promotion expenditure	Rwanda Development Board (RDB)
Distance	Google using distance calculator
Political stability Index	GlobalEcomony.com

Methods

Though several attempts have been made to identify factors affecting tourism demand (Claveria et al., 2015; Huang & Hao, 2021; Kilimci et at., 2019; Law, 2000), the main focus has been put on forecasting tourism arrivals using various machine learning techniques such deep learning approach (Kilimci et al., 2019), back propagation (Law, 2000), search engine and ensemble support vector regression (Huang & Hao, 2021) and Artificial Neural Network Models (Claveria et al., 2015). Therefore, the current study compares the results of Radom forest and linear regression using RMSE and R- squared to identify the main determinants of tourism demand. Random forest modes have recently stimulated the interest of researchers from a variety of industries (Genuer et al., 2017; Hapfelmeier & Ulm, 2014). They are appreciated because they can handle large amounts of data to extract small sets of variables and ascertain variable relevance (Matin et al., 2018). One of the AI-based forecasting techniques is the regression tree. Because of their non-parametric structure, they can easily create regression trees, which is a significant advantage (Cankurt, 2016). Decision Trees (DTs) are a nonparametric supervised learning algorithm that can be used to solve classification and regression problems (Wang et al. 2004).

Econometric forecasting models have played a significant role in tourism demand forecasting research over the last five decades. In the most basic econometric forecasting model, a single static regression is used (SR). The main goal of such fundamental models is to determine how various variables contribute to the current values. To avoid the spurious regression problem, the variables in these regressions are normally expected to be stationary. This category contains many of the early studies on tourism demand (Martin & Witt, 1988). In recent years, linear regression has thus been used as a standard for evaluating tourism demand forecasting.

Variables definition

Table 2. Description of different variables used in the models

Variable name	Variable description
pol_sta	Political Stability index
CPI_rda	Consumer Price Index in Rwanda (USD)
prec_rda	Monthly Precipitation (mm)
prom_exp_rda	Monthly promotion expenditure (USD)
temp_rda	Temperature (0°C)
dist_rda	Distance between Rwanda and the country of origin of the tourist (km)
trend	Trend used to capture the effects of time on tourism arrivals
Month_ January	January
Month_ February	February
Month _March	March
Month_ April	April
Month_May	May
Month_June	June
Month_July	July
Month_August	August
Month_September	September
Month_October	October
Month_November	November
Month_ December	December
RegionofResidence_orig_Africa	America
RegionofResidence_orig_Americas	America
RegionofResidence_orig_Asia	Asia
RegionofResidence_orig_Europe	Europe
RegionofResidence_orig_Middle East	Middle East
RegionofResidence_orig_South Asia	South Asia
ModeofTransport_Air	Air Transport
ModeofTransport_Road	Road Transport
PurposeOfVisit_Business	Business
PurposeOfVisit_Conference	Conference
PurposeOfVisit_Education	Education
PurposeOfVisit_Holiday	Holidays
PurposeOfVisit_Medical	Medical
PurposeOfVisit_Mission	Official mission
PurposeOfVisit_Other	Others
PurposeOfVisit_Resident	Resident
PurposeOfVisit_Transit	Transit
PurposeOfVisit_Visit	Visit to Friends and relatives
covid-19_0	Covid-19
visa_0	Introduction of VISA in 2018
visa_1	Introduction of VISA in 2018

Dependent variable: The total numbers of arrivals by purpose of visit has been consistently used as the dependent variable (Peng et al., 2015; Kim et al., 2018).
Independent variables: Various independent variables were included in the models to evaluate their degree of importance to explain the total number of tourism arrivals.

These variables include consumer price index (USD) that is used as a proxy of price (Peng et al., 2014; Kim et al., 2018), tourism promotion expenditure incurred by Rwanda Development Board (Adeola et al., 2018; Peng et al., 2015); temperature (0°C) and precipitation (mm) (Kumar, 2020; Tavares & Leitao, 2017), distance (Km) (Tatoglu & Gul, 2019 ; Permatasari & Padilla ,2020); political stability index (Peng et al., 2015; Vanegas et al., 2020); trend to capture the effect of time on the total number of arrivals; a dummy variable to capture the effect of the introduction of VISA on arrivals since January 2018; a dummy variable to capture the effects of COVID-19; dummy variables to capture the effect of different modes of transports ; dummy variables to capture the effect of different regions of tourists' residence and the dummy variables to capture the effect of the months of the year.

Results and discussion

The aim of this research was to identify factors that influence tourism demand using machine learning techniques. The results of random forest and linear regression models on both the train and test sets were compared using Root Mean Square Error (RMSE) and R-Squared to determine the extent to which different variables included in the model can better contribute to the prediction of tourism demand.

The evaluation of the level of accuracy of each model used in the current study plays a critical role to determine the extent to which each model can accurately predict the determinants of tourism demand. This is accomplished by comparing the actual values to the projected values of the model. The generalization of the model to the new data should also be assessed, which is accomplished by dividing the dataset into two sets, one for training set and the other for testing set. In the current study, the most commonly used approaches for evaluating model accuracy, Root Mean Square Error (RMSE) and R-square (R^2) were used.

The standard deviation of the residuals is defined as the Root Mean Square Error (RMSE) (prediction errors). Before calculating the RMSE, the errors need to be squared to reduce the variance. The differences between the expected and actual values are referred to as residuals. The RMSE is among the most commonly used measures of the distribution of residuals. The root mean square error (RMSE) plays an important role to minimize errors while forecasting in the case of severe variances or residuals.

$\boldsymbol{R^2}$: The R-square (R^2) is a statistical measure of how much variance is accounted for in a relationship between two (or more) variables. This metric shows how well a model fits the data and how closely projected values match actual values. The R squared values vary from 0 to 1, with 0 indicating that the model does not match the data and 1 indicating that the model fits the data well (100 percent).

The results of model evaluation

To test generalizability of the model to new data, the data was divided into two parts: one for training and one for testing the trained model. The train set consisted of data from January 1, 2007 to May 31, 2019, while the test data ranged from June 1st, 2019 to September 1st, 2021.

Table 2 displays the outcomes of model evaluation for both the training and test sets. On a training set, the root mean squared error of linear regression is 0.434. The R-square of linear regression is 0.811 on the train set and -5.047 on the test set. The linear regression model can accurately predict the number of tourist visitors on the train set with an accuracy of 81 percent, but it failed to predict tourism demand using data on the test set.

Table 3: Model evaluation results

Model	Set	RMSE	R-square
Linear Regression	Train	0.434	0.811
	Test	2.25E+11	-5.047
Random Forest	Train	0.2211	0.951
	Test	0.529	0.719

The root mean squared error of the random forest is 0.2211 on a train set and 0.529 on a test set. In the same vein, the R-square of the random forest is 0.951 on a train set and 0.719 on a test set. This means that the model can accurately predict the number of tourist visitors at a level of 95 percent on the train set and 72 percent on the test set. As a result, despite the training set containing data with different behavior than the previous time due to the effects of COVID-19 on tourism arrivals, the model made better predictions on both the training set (95 percent) and the test set (72 percent).

Features importance using random forest

Figure 1 below portrays the feature importance of different variables to explain the number of tourism arrivals using random forest. As indicated by the figure, the main variables to explain the total number of arrivals are temperature (26 percent); consumer price index (25 percent); political stability (8.8 percent); distance (7.5 percent); precipitation (7.3 percent); region of Residence-Africa (8.7 percent); promotion expenditure (4 percent) and region of Residence-Europe (4 percent).

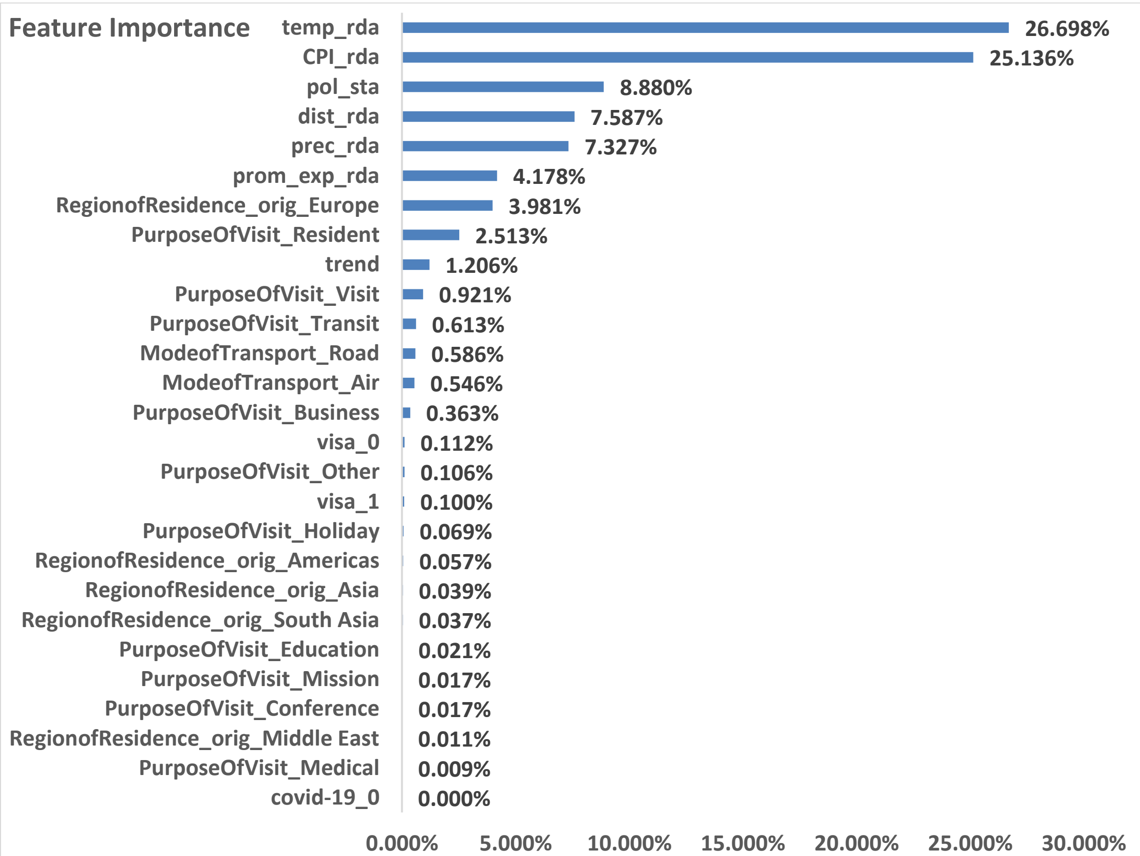

Figure 1. Factors affecting tourism demand

Unlike Africa (8.7 percent) and Europe (4percent), other regions of residence such as America (0.06%), South Asia (0.04) and Middle East (0.01%) appeared to have a relatively small influence on the number of arrivals. Other regions of residence, such as America (0.06%), South Asia (0.04), and the Middle East (0.01%), appeared to have a relatively small influence on the number of tourism arrivals in contrast to Africa (8.7%) and Europe (4%). Though the main purpose visits have a relatively small explanatory power compared to other important factors, the main purposes of visit that outperformed others include residents (2.5%); visits to friends and relatives (0.99%); transit (0.61%) and business (0.36%). Though the introduction of the VISA on arrival policy has a relatively small explanatory power (0.1%) when compared to other important factors, its explanatory power remains rrlatively significant in influencing tourism arrivals. Though the trend has been among important features to explain tourism arrivals (1.21%), various months of the year had very little influence on the number of tourism arrivals compared to other important factors that were identified to impact the total number of tourism arrivals (see table 2 below). Surprisingly, COVID-19 in general had very little impact on tourism arrivals. One possible reason for explaining this is that since the outbreak of COVID-19, the government of Rwanda has been putting in place COVID-19 containment measures that are in favour of the tourism sector, and this is evident because the tourism sector is among the main contributors to GDP and job creation.

Table 4. Estimating determinants of tourism demand using Random Forest

Variable	**Feature importance (%)**
Temperature	26.7
Consumer price Index Rwanda	25.14
Political stability	8.88
Region of Residence-Africa	8.76
Distance between the country of origin and Rwanda	7.59
Precipitation in Rwanda	7.33
Promotion expenditure	4.18
Region of residence -Europe	3.98
Purpose of visit-Residents	2.51
trend	1.21
Purpose of visit-Visit to Friends and Relatives (VFR)	0.92
PurposeOfVisit_Transit	0.61
Mode of Transport-Road	0.59
Mode of Transport- Air	0.55
Purpose of visit –Business	0.36
visa_0	0.11
Purpose of Visit-others	0.11
visa_1	0.10
Purpose of visit-Holidays	0.07
Region of residence-America	0.06
Region of residence-Asia	0.04
Region of Residence_orig_South Asia	0.04
Purpose of visit-Education	0.02
Purpose of visit-Mission	0.02
Purpose of visit-Conference	0.02
August	0.02
July	0.01
January	0.01
Region of Residence –Middle East	0.01
November	0.01
March	0.01
Purpose of Visit-Medical	0.01
May	0.01
April	0.01
December	0.01
October	0.01
June	0.01
February	0.00
Month_September	0.00
covid-19_0	0.00

Conclusions

The purpose of the current study was to determine factors affecting tourism demand using machine learning techniques. The random forest model outperformed the linear regression model on both the train and test sets. The linear regression model was able to accurately predict the number of visitors on the train set but failed to better predict tourism demand using data on the test set. Unlike linear regression, the random forest models made better predictions on both the training and test sets, despite the fact that the test set contained data with different behaviors than the previous time due to the effects of COVID-19 on tourism arrivals.

Climate (Kumar et al., 2020), consumer price index (Peng et al., 2015), political stability (Vanegas et al., 2020), distance, promotion expenditure (Adeola et al., 2018), and region of residence are all important factors in explaining total arrivals. The findings of the current research, therefore, provide additional evidence for the effectiveness of the AI based models to improve tourism demand forecasting compared to linear regression models.

As the introduction of the visa on arrival policy has proven to have some influence on the total number of tourism arrivals, more policy reforms need to be thought through especially targeting the promotion of various forms of inbound and outbound tourism that are still underdeveloped such as cultural tourism, community-based tourism, medical tourism and sport tourism. One of the most significant findings to emerge from this study is that promotion expenditure was statistically significant to explain the number of arrivals. Therefore, policymakers need to double efforts to expand and sustain ongoing tourism promotion campaigns such as visiting Rwanda, Tembera URwanda, Kwita Izina especially targeting inbound tourism and some regions of world from which Rwanda has proven to attract a relatively small number of tourists. Another major finding that emerged from this study is that climate appears to be one of the most important factors to attract tourists. This implies that policymakers should enhance and sustain ongoing policy reforms geared towards environment and biodiversity protection.

This study was limited by the absence of highly frequent data, such as daily data. The initial plan was to use highly frequent data, such as weekly or daily data. However, given that daily data is not consistently collected, it appeared hard to use it. Therefore, future research would explore the possibility of using high-frequency data to improve the efficiency of the tourism demand forecasting models. The study is also limited by the lack of information on monthly data on variables such Gross Domestic Product and exchange range, demographic information of the respondents, the price of substitutes and the visitor's travel habits and the visitor tastes and preferences. Therefore, further work needs to be done to establish whether the inclusion of these variables would improve the predictive power of the AI based models to predict tourism demand. More broadly, research is also needed to explore emerging topics in the context of Rwanda such as inbound tourism, medical tourism, cultural tourism and sport tourism.

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