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Forecasting International Tourist Arrival in Nepal by ARIMA Model

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Abstract

To project Nepal's tourism growth from 2024 to 2028, use the ARIMA (1,0,0) model. It is crucial to comprehend the model's efficacy and precision in approximating both short- and long-term patterns of tourism inflows. The results show how effective the ARIMA model is, explaining 82.4% of the variations in the data, or the stationary $R^2 = 0.824$. The suitability of the model and the correlation between its residuals were confirmed by the Ljung-Box test (Statistic = 6.657) and run test (Sig. = 0.988). Due to a strong correlation between the number of visits from the previous month and the number of arrivals this month, the AR(1) parameter was highly significant ($p < 0.001$). Based on anticipated findings, the trend of tourism inflows appears to be improving. The number of visitors is likely to reach 1,045,196.40 in 2024 and is projected to increase even further to 1,156,987.09 in 2028. Confidence intervals show that by 2028, the number of tourists may be as low as 179,546.91 or as high as 4,062,926.89, highlighting the difficulties in estimating long-term numbers. Additionally, the risk of external diversification factors, such as the political and economic environments, which may either facilitate or obstruct the progress of tourism, is typically associated with the expanding gap between the lower and upper confidence limits. Based on anticipated findings, the trend of tourism inflows appears to be improving. The number of visitors is likely to reach 1,045,196.40 in 2024 and is projected to increase even further to 1,156,987.09 in 2028. Confidence intervals show that by 2028, the number of tourists may be as low as 179,546.91 or as high as 4,062,926.89, highlighting the difficulties in estimating long-term numbers. Additionally, the risk of external diversification factors, such as the political and economic environments, which may either facilitate or obstruct the progress of tourism, is typically associated with the expanding gap between the lower and upper confidence limits.

Keywords: ARIMA Model, International Tourism, Forecasting, Nepal, Time Series Analysis

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Introduction

One of the most significant sources of income for Nepal is tourism, which also develops the area and offers job possibilities. Essential items for Nepalese tourism include the country's breathtaking Himalayan range, which draws millions of visitors each year, as well as cultural and historical sites. Owing to the importance of tourism, a dependable technique for estimating the number of visitors arriving in the tourism industry must exist. This can support many stakeholders in efficiently managing resources, organizing marketing campaigns, and building infrastructure that is within people's reach in an ideal way.
As a result, the ARIMA model has become the most often used forecasting technique due to its ability to handle time series data effectively. The primary aim of this study is to forecast tourist arrivals to Nepal using the ARIMA model. The results of this analysis may be helpful to those involved in the tourism sector.

Tourism in Nepal is quite important in terms of the economy of country. Before the outbreak of the COVID-19 pandemic in 2020, international arrivals in Nepal in 2019 were 1 19 million visitors, and earnings estimates of nearly USD 724 million (Nepal Tourism Board, 2020). The sector also reveals commendable performance in employment, as it is directly involved in the support of more than 1. 500 thousand in 2018, which is 6 percent higher as compared to 2017, and reached up to 06 million jobs in 2019. Employment of people: 9% of total employment employees are engaged in the travel & tourism sector (WTTC, 2019). The above stats also imply the significance of developing comprehensive tourism forecasting techniques that can help in identifying the future trends and plan on the same accordingly.

Early in 1973, Box and Jenkins created the ARIMA model, which quickly rose to prominence as one of the most well-known and extensively applied time series forecasting techniques. For the majority of time series data analysis applications, the ARIMA model is incredibly adaptable and powerful. It consists of three primary parts: Specifically, we will talk about moving average (MA), autoregression (AR), and differencing to make the series stationary (integrated, I).
Establishing regression of the variable with the variable's lag or past values is necessary for the AR component. By using a moving average model based on previous observations, the MA component attempts to replicate the relationship between an observation and a residual error.

Thus, the number of lag observations in the model (AR portion) corresponds to the order of the autoregression model, represented by p. The number of times the raw observations have differed (I portion) is denoted by d.In this particular model component, the moving average window (MA portion) size was represented by the value of the variable (Box, Jenkins, & Reinsel, 2008).

Since it serves as the foundation for the creation and development of strategies for the tourist sector, scholarly research on tourism demand forecasting has drawn a lot of interest. Other methods, ranging from the basic, like naïve models and exponential smoothing approaches, to the sophisticated, such as machine learning models, have been employed to predict the number of tourists. Nonetheless, because of its effectiveness and simplicity in identifying the linear component of time series data, the ARIMA model is still in use today.

The ARIMA model has been proven to be useful for forecasting tourism in earlier studies. Chu (1998) demonstrated that the ARIMA model is useful for short-term forecasting by using it to predict the demand for tourism in the Asia-Pacific region. Consequently, the primary benefits of the employed model became apparent: its capacity to accurately represent the underlying patterns and inclinations that are crucial to the forecasting process. Nevertheless, due to its ease of use and effectiveness in determining the linear component of time series data, the ARIMA model is still in use.

The ARIMA model has been validated for use in forecasting tourism in earlier research studies. Chu (1998) utilized ARIMA to predict the tourism demand for the Asia-Pacific region, demonstrating the model's efficacy in short-term forecasting. The capacity to fit the true deeper pattern and tendencies that are crucial to the forecasting process thus demonstrates the primary benefits of the employed model. Businesses and tourism authorities in Nepal may find it helpful to research using the ARIMA model to forecast visitor arrivals. A few issues that impact tourism in Nepal are the changing seasons, political unrest, and natural disasters like earthquakes. However, since good forecasting promotes better resource allocation and preparation, these difficulties can be handled.

The following factors, among others, affect the pattern or flows of foreign immigration in Nepal: the climate, cultural festivals, and events. For instance, the spring, which runs from March to May, and the fall, which runs from September to November, are the tourist seasons with the highest volume of travel. By applying the ARIMA model to truly understand these seasonal trends, the stakeholders would be able to improve their marketing and operations plans.

However, natural disasters and geopolitical unrest have had a significant impact on Nepal's tourism industry. For example, the 2015 earthquake reduced the amount of tourists coming to this country due to losses from stocks and other appealing locations, as well as worry that the earthquake would return. Thus, an accurate identification of these shocks and trends using an ARIMA model can enhance the forecast and foster more favorable conditions for the economy and government to recover and grow further.

Statement of the Problem

Numerous writers have confirmed that the ARIMA model is a reliable tool for estimating visitor arrivals. For example, Upadhayaya (2021) reported that an ARIMA (1,1,1) model best matched the monthly arrival data from Nepal for the years 2000 to 2020, supporting the claim that accurate forecasts are necessary for strategic planning in Nepal's tourism industry. The model's capacity for seasonal forecasting, which is essential for the management of tourism resources, was also mentioned by Sharma & Ghimire **(2019).** Similarly praised the ARIMA model was praised, pointing out that it can be included in policy decisions because it is appropriate for short-term forecasting. To improve forecasts during exogenous shocks, Subedi (2017) further—and maybe controversially—extended the ARIMA model by incorporating an evaluation of world events like natural disasters and political crises as part of the forecasting model. They argue that in a particular context—the growth of tourism in southern Asia—this model can also be effective for short-term tourist forecasting. Khatri (2024) made the point that to guarantee that tourism in Nepal grows in a balanced manner, it is necessary to examine the seasonal fluctuations in visitor numbers.

Upadhayaya (2021) recognized a few shortcomings, such as the model's capacity to adjust to unforeseen events and issues with the data. However, they confirmed that it is a reliable tool for trend prediction. Going one step further, Pradhan & Koirala (2024) showed proof of the model's applicability in a variety of economic scenarios with workable solutions for the travel and tourist sector.

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Objectives

- To explore international tourist arrivals in Nepal from 2024 to 2028 by applying the ARIMA model.
- To assess the effectiveness and dependability of the ARIMA model in forecasting the inflow of tourists in the short and long run.

Research Questions

- What patterns of foreign visitor arrivals to Nepal are anticipated by the ARIMA model for the years 2024–2028?
- How reliable is the ARIMA model for predicting foreign immigration to Nepal during short periods (1-2 years) and long periods (3+ years)?
- What will be the cause of the ARIMA model's effective use in predicting Nepal's influx of tourists?
- What are the drawbacks and uncertainties in employing an ARIMA model to anticipate foreign visitor arrivals over an extended period?

Literature Review

To project, Shrestha tested the ARIMA model on foreign visitor arrivals to Nepal using monthly data for the years 2000 to 2020. The results indicated that the ARIMA model of order (1,1,1) fit the data well. Accurate forecasts are crucial for developing strategic plans for Nepal's tourism industry, and this study has done a great job of emphasizing this need.

Upadhayaya (2021), for instance, examined time series data on visitor arrivals in Nepal while working on the ARIMA model. According to their analysis, the ARIMA model accurately predicted the near-term and caught seasonal patterns, both of which are crucial for managing tourism resources.

Pradhan & Koirala (2024) used ARIMA and a few other time series models to estimate the demand for tourism in Nepal; they observed that the ARIMA model is most useful for short-term forecasting and highlighted its potential application as a source of information for policy decisions.

Subedi (2017) examined the effects of worldwide events, such as natural disasters and political upheavals, on the quantity of visitors to Nepal. Subedi provided an example of how to use the ARIMA model to capture such exogenous shocks and improve forecasting accuracy.

Khatri et. al (2024) used the ARIMA model to evaluate the seasonal variance in visitor arrivals to anticipate future trends. The study places even more emphasis on how crucial it is to comprehend seasonality to manage tourism sustainably in Nepal.

Using the ARIMA model, Khatri et. al (2024) projected the demand for tourism throughout South Asia, with a particular emphasis on Nepal. According to the study, the ARIMA model is useful when planning regional tourism and is especially applicable for short-term forecasting., K.C. et.al. (2024) examined the limitations and potential of the ARIMA model concerning Nepal's tourist projections.

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While unexpected occurrences and data issues were identified as one of the publication's primary issues, the publication's strength in trend prediction was also confirmed.

The ARIMA model was used by Khatri et. al (2024) to establish tourism trends in Nepal, and they praised it for its ability to accurately capture the dynamics surrounding visitor arrivals. This study has contributed to the body of literature by providing a detailed examination of the model's advantages and disadvantages.

Using data from 1990 to 2015, Pradhan & Koirala, (2024**).** used an ARIMA model to anticipate the number of tourists that would arrive in Nepal. Their research provided a valuable understanding of the model's predictive capacity and its application to Nepal's tourism administration.

Shah and Tiwari (2021) used the ARIMA model to empirically analyze the forecasting of tourism demand in Nepal. Their findings supported the model's applicability in various economic circumstances and offered suggestions for tactics that the tourism industry may use.

Methodology

The following actions will be conducted to use the ARIMA model to forecast the number of tourists that will arrive in Nepal: The following actions will be conducted to use the ARIMA model to forecast the number of tourists that will arrive in Nepal.

Data Collection: The Nepal Tourism Board and other relevant organizations' previous years' records will be mined for primary data on the number of tourists arriving in Nepal every month. The data must span a long enough time to account for the business's trends and tendencies.
Preprocessing of the Data: After the data has been gathered, it will be cleaned to remove any missing values, outliers, and inconsistent records. The seasonal components may be analyzed and visualized using period decomposition.

Stationarity Check: The characteristics of the time series data under examination will be analyzed using the Augmented Dickey-Fuller (ADF) test and/or differencing. If the data is not stationary, we will apply the differencing approach until the data becomes stationary. (Dickey & Fuller, 1979).
Model Identification: The ACF and PACF plots, among other visualization tools, will be used to ascertain the values for the ARIMA model's parameters (p), (d), and (q). (Dickey & Fuller, 1979).
Model Estimation: The ARIMA model will be estimated using the established parameters. By gauging the degree of fit using metrics like the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), the models to compare can be chosen. (Dickey & Fuller, 1979).

Model Validation: A subsystem of data that is separated from the database will be used to test the chosen model. To assess the efficacy of the model, additional variables such as Mean Absolute Error and Root Mean Squared Error will be utilized.

Forecasting: The model will be used to project future tourist arrivals after it has been validated. The directional values will be forecasted further to provide the stakeholders with information.

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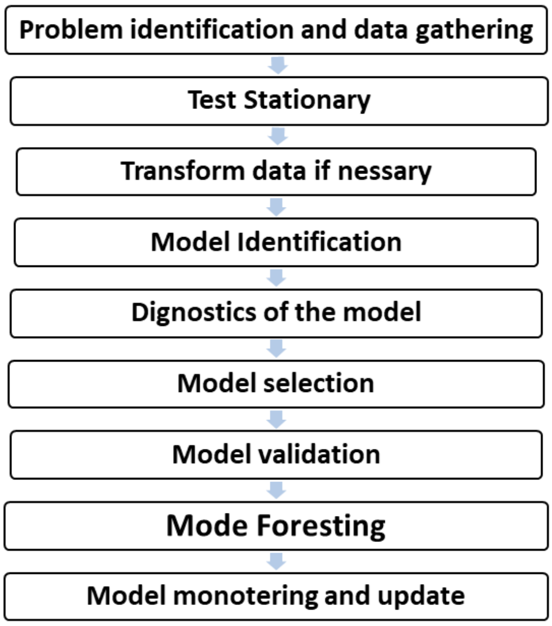
Flow- Chart of ARIMA model conducting process



Anticipated Results and Consequences

Therefore, the following significant results could arise from the ARIMA model's prediction of visitor arrivals in Nepal. Initially, it will provide reliable and credible projections of the anticipated number of visitors, which can help the tourism and business authorities. This can result in better infrastructure support, appropriate marketing strategies, and efficient use of resources. (Song & Li, 2008).

Secondly, the projections facilitate the management of the seasonality of the tourist flow, an essential aspect to consider while strategizing the growth of a nation's tourism industry. The stakeholders benefit from seasonal variation in that it allows them to better arrange for peak business periods and decrease waste resulting from slower business periods. (Lim & McAleer, 2002).

Third, the ARIMA model can be used to warn of externalities that could have a detrimental impact on the nation's economy, such as political unrest and natural disasters. By incorporating these shocks into the model, the forecasts produced will be much more accurate, enabling better protection and a much faster recovery. (Zhou & Zhang, 2020).

Finally, the results obtained from the ARIMA model can contribute to the development of sustainable tourism in Nepal. With the use of this tool, the provided model will show how tourism may grow in a way that is both efficient and beneficial to the nation's economy, allowing for the potential value of the nation's natural resources and cultural heritage to be taken into account. (Butler, 1999)

In light of the foregoing debate, it is now possible to conclude that, with regard to Nepali tourism, anticipating tourism is a crucial component of strategic management and planning. An accurate model for predicting the number of tourists arriving is the ARIMA model, which is designed exclusively for time series data. By utilizing the ARIMA model, this study hopes to provide a forecast that will help stakeholders plan strategically in the tourism sector so that resources may be used wisely and the industry's growth is sustained. (Box & Jenkins, 1976).

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Thus, there is great potential for the ARIMA model that has been proposed to estimate the arrival of tourists in the Nepalese market. Since this is a learning model, it can identify trends in the data that can aid in characterizing and growing Nepal's tourism industry. (Song & Li, 2008) By using higher-level models and examining additional factors like marketing campaigns and worldwide market conditions that may have an impact on tourist arrivals, future research can build on this study. (Li, Song, & Witt, 2005).

Table 1

Data recorded by the Nepal Tourism Board is presented as follows

Year	No. of Tourist
1964	9526
1965	9388
1966	12567
1967	18093
1968	24209
1969	34901
1970	45970
1971	49914
1972	52930
1973	68047
1974	89838
1975	92440
1976	105108
1977	129329
1978	156123
1979	162267
1980	162897
1981	161669
1982	175448
1983	179405
1984	176634
1985	180989
1986	223331
1987	248080
1988	265943
1989	239945
1990	254885
1991	292995
1992	334353
1993	293567
1994	363394
1995	363393
1996	393613
1997	421857

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1998	463684
1999	491504
2000	463646
2001	631237
2002	275468
2003	338132
2004	385297
2005	375398
2006	383926
2007	526705
2008	500277
2009	509956
2010	602867
2011	736215
2012	803092
2013	797616
2014	790118
2015	538970
2016	753002

Analysis of the Data and Presentation of the Result
Plotting a graph of original data

Table 2

Case Processing Summary

Case Processing Summary		Tourist
Series or Sequence Length		61
Number of Missing Values in the Plot	User-Missing	0
	System-Missing	8

Graph representing tourists arrived in different years

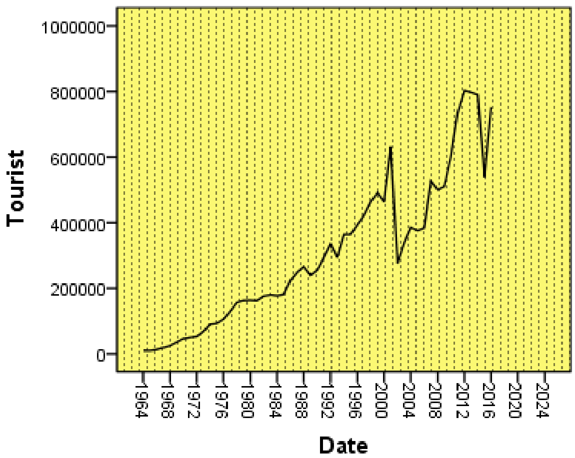

Figure No. 1

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After analyzing the above graph The time series chart of the number of visitors to Nepal between 1964 and 2024. The data displayed in the plot can be interpreted as follows:

Trend Analysis:

Long-term Growth: Over the years, it has been observed that the number of tourist arrivals in Nepal has been increasing or decreasing. From as little as zero-one in the 1960s, the overall figure & rate presents a progressive increase.

Periodic Peaks and Troughs: While the general trend demonstrates steady growth, it is rather oscillative and can be characterized by certain peaks and valleys.

Given time series is not stationary. to make it stationary, take the difference between the values until the series is not stationary.

Graph of time series after one differentiation

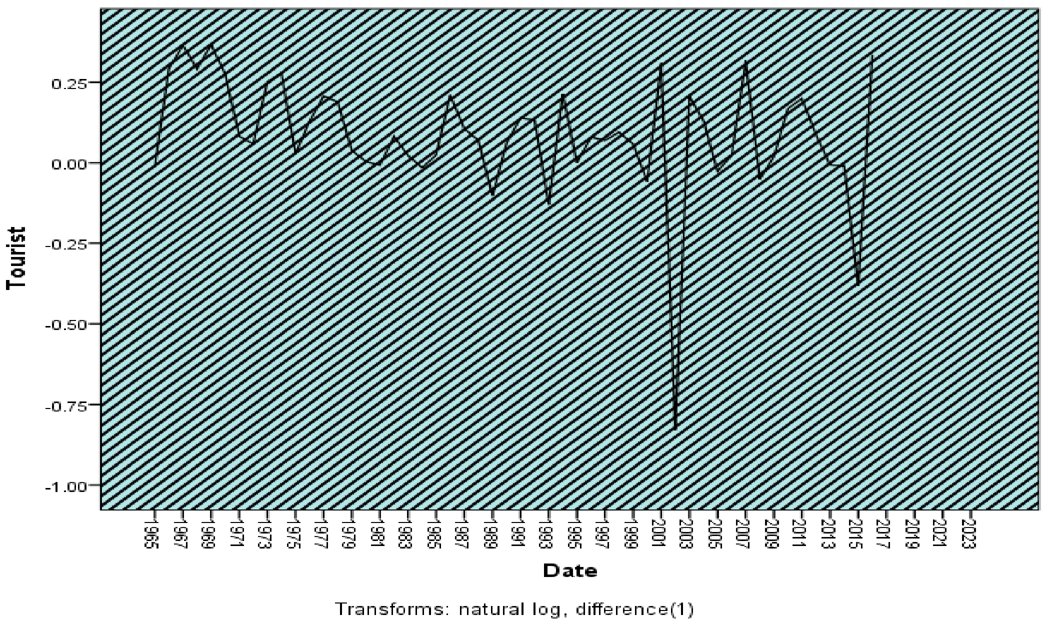

Figure No. 2

This figure does not look like stationary. Further, take differentiation to make it stationary

The above figure looks like stationary. To confirm it we have to test stationary

Stationarity Check: The characteristics of the time series data under examination will be analyzed using the Augmented Dickey-Fuller (ADF) test and/or differencing. If the data is not stationary, we will apply the differencing approach until the data becomes stationary.

Model Identification: The ACF and PACF plots, among other visualization tools, will be used to ascertain the values for the ARIMA model's parameters (p), (d), and (q).

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Table 3

Stationarity Tests

Test	Statistic	Truncation lag parameter	p	H_0
Augmented Dickey-Fuller t	-4.324	3	0.010 [a]	Non-stationary
Phillips-Perron regression coefficient ρ	-30.262	3	0.010 [a]	Non-stationary
Phillips-Perron studentized τ	-4.512	3	0.010 [a]	Non-stationary
Kwiatkowski-Phillips-Schmidt-Shin Level η	0.163	3	0.100 [b]	Level stationery
Kwiatkowski-Phillips-Schmidt-Shin Trend η	0.073	3	0.100 [b]	Trend stationery

Table 4

Autocorrelations

			Box-Ljung Statistic		
Lag	Autocorrelation	Std. Error[a]	Value	df	Sig.[b]
1	-.547	.136	16.183	1	.000
2	.057	.135	16.362	2	.000
3	.016	.133	16.376	3	.001
4	.076	.132	16.706	4	.002
5	-.189	.130	18.796	5	.002
6	.100	.129	19.400	6	.004
7	.117	.128	20.243	7	.005
8	-.242	.126	23.928	8	.002
9	.177	.125	25.938	9	.002
10	-.021	.123	25.965	10	.004
11	-.042	.122	26.084	11	.006
12	-.147	.120	27.573	12	.006
13	.410	.119	39.559	13	.000
14	-.322	.117	47.119	14	.000
15	.100	.115	47.864	15	.000
16	-.073	.114	48.274	16	.000

A high autocorrelation for the series at various lags might indicate that it is not, in fact, a random process but white noise. It, on the other hand, reflects the latent dependencies or patterns of the data. The most obvious correlations are the negative autocorrelation at lag 1, the significant positive at lag 13, and the negative at lag 14. Significant Box-Ljung statistics up through lag 16 with low P-values confirm some kind of non-random structure in the time series.

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This could be used to indicate that historical visitor count, up to about 16 periods in the past, has predictive potential for future values, which is informative for the kind of improvements to be made in a simple forecasting model. These models can be fitted with strong autocorrelations at specific lags so that they are more accurate.

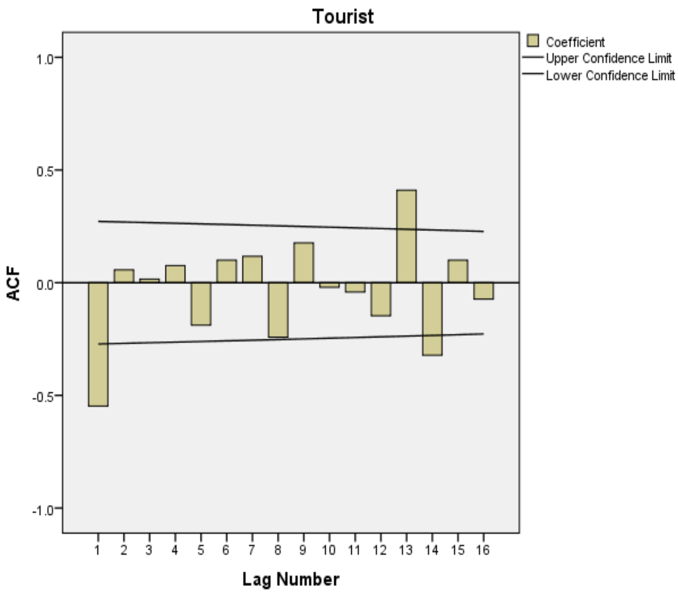

Figure No. 3

Table 5

Partial Autocorrelations

Lag	Partial Autocorrelation	Std. Error
1	-.547	.140
2	-.346	.140
3	-.213	.140
4	.001	.140
5	-.181	.140
6	-.172	.140
7	.090	.140
8	-.146	.140
9	-.026	.140
10	.014	.140
11	-.023	.140
12	-.251	.140
13	.224	.140
14	.093	.140
15	.112	.140
16	-.123	.140

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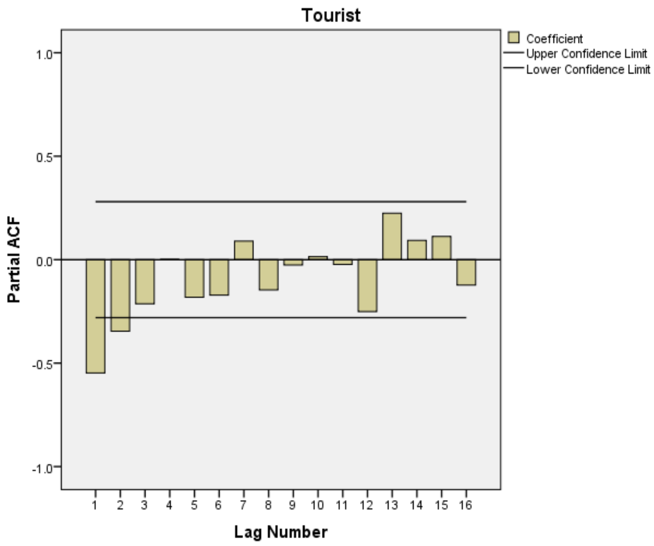

Figure No. 4

Large partial autocorrelations at lags 1, 2, 3, 12, and 13 suggest that information about the time series structure is contained in this lag. While the values at lags 12 and 13 may be the consequence of seasonal influence or another longer-lasting periodic pattern, high values at lags 1 and 2 demonstrate short-term dependency. The weaker association that could not be significant is indicated by the tiny partial autocorrelations at various lags.

Positive values at lag 13 show a strong direct association, while negative partial autocorrelations at early lags, 1 to 3, imply an inverse relationship. In a time series model like ARIMA, the information above can be utilized as a guide when choosing the AR terms. An AR (1) model, for instance, might be suggested by a substantial partial autocorrelation at lag 1, but other significant delays might force one to take into account more variables.

Possible ARIMA Model Identification

We may recognize ARIMA models based on the autocorrelation and partial autocorrelation functions. The following outlines the key takeaways from ACF and PACF: At lag 1, there were notable negative autocorrelations.

At lag 13, there are notable autocorrelations.

Partial autocorrelations are visible at lags 1, 2, 3, 12, and 13.
These results suggest that seasonal impacts and autoregressive components should be included.

ARIMA (1,0,0)

Reason: An AR (1) model may be appropriate given the significant partial autocorrelation at lag 1 and the negative autocorrelation at lag 1.

$$X_t=\phi_1 X_{t-1}+\epsilon_t$$

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ARIMA (2,0,0) (AR(2)):

$$X_t=\phi_1 X_{t-1}+\phi_2 X_{t-2}+\epsilon_t$$

The strong partial autocorrelation of the PACF at lags 1 and 2 is the cause of this. An AR(2) model could account for these dependencies.

ARIMA (0,0,1) (MA(1)):

$$X_t=\epsilon_t+\theta_1\epsilon_{t-1}$$

In the ACF, there is a strong negative autocorrelation at lag 1; hence, it can suggest a moving average component. This behavior will be captured by the MA (1) model.

ARIMA (1,0,1) (ARMA (1,1)):

$$X_t=\phi_1 X_{t-1}+\epsilon_t+\theta_1\epsilon_{t-1}$$

The series may follow a mixed model with both AR and MA components, as seen by the significant autocorrelation and partial autocorrelation observed at lag 1.

Table 6

Criteria for choosing the best ARIMA model

Statistical Value	ARIMA (1,0,0)	ARIMA (2,0,0)	ARIMA (0,0,1)	ARMA (1,0,1)	Remark
StationaryR squared	0.896	0.891	0.591	0.888	
R-squared	0.633	0.542	0.593	0.581	
RMSE	139366.770	157197.699	146774.935	150434.618	
MAPE	173.412	197.940	130.041	188.768	
MaxAPE	8472.122	9772.755	2997.407	9288.395	
MAE	56395.084	59895.458	106218.358	58191.633	
MaxAE	807054.331	930952.672	473418.869	884812.509	
Normalized BIC	23.840	24.155	23.943	24.067	

After analyzing tabulated values in the above table, ARIMA (1,0,0) is considered the best model because it has stationary R^2 and $R^2$are highest as compared to other models and all types of error values are minimum as compared to other models.

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Results of ARIMA Forecasting

Table 7

Model Statistics

		Model Fit Statistics	Ljung-Box Q(18)			
Model	Number of Predictors	Stationary R-squared	Statistics	DF	Sig.	Number of Outliers
Tourist-Model_1	0	.824	6.657	17	.988	0

R-squared stationary = 0.824: This statistic measures how well the model fits the data without any trends or stationarity. With a score of 0.824, the model can explain 82.4 percent of the variation of the fitted stationary series, suggesting a decent fit.

The Ljung-Box test statistic, Statistics = 6.657, determined whether or not the model residuals, or mistakes, were autocorrelated. A substantial piece of data may be missing from the model if the residuals are shown to be autocorrelated.
The run test had 17 degrees of freedom (DF = 17).Sig. = 0.988:

The test predictive value of 0.988 was determined by the result. When there is little to no autocorrelation with the residuals, a p-value of more than 0.05 indicates that the residuals The absence of outliers, or the absence of unusual or severe data points that could have distorted the model's accuracy, was the conclusion of the model are essentially random.

Table 8

ARIMA Model Parameters

				Estimate	SE	t	Sig.
Tourist-Model_1	TouristNatural Log	Constant		11.841	1.843	6.427	.000
		AR	Lag 1	.982	.026	38.407	.000

The variable of interest, visitor arrivals, has been shifted so that the value of the natural log is utilized. When working with time series data, this is a frequent practice where an attempt is made to make the data more orientated toward the normal distribution, which makes it more suitable for ARIMA modeling.

Estimate = 11.841: This is the model's estimated constant, also known as the intercept. It is the arrivals of tourists expressed as their natural logarithm in the absence of any other influences (such autoregressive terms).
The constant estimate's standard error is equal to 1.843. A lower SE suggests that the estimate was more precisely calculated.

t = 6.427: The t-statistic determines whether the constant deviates significantly from zero.

Sig. =.000: Because of the constant's highly significant p-value ($p < 0.001$), the constant term is required and does not equal zero.

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The model shows a very strong correlation between the variables at lag 1, with visitor arrivals in a given period being almost entirely explained by those from the preceding period (AR(1)=0.982). Furthermore, important is the constant phrase. Low p-values for the parameters indicate their significance in the model and the statistical reliability of the predictions. Given the high importance and accuracy of the parameter estimates, it is thus a suitable model that may reliably predict future visitor arrivals.

Table 9

Forecast

Model		2024	2025	2026	2027	2028
Tourist-Model_1	Forecast	1045196.40	1074606.00	1103066.88	1130538.60	1156987.09
	UCL	2017369.38	2603650.76	3123840.99	3606986.85	4062926.89
	LCL	475321.91	343311.70	267072.35	216151.57	179546.91

For each model, forecasts start after the last non-missing in the range of the requested estimation period and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

To achieve the intended results in this output, which is forecasting the number of tourists arriving shortly, the ARIMA model—specifically, the Tourist-Model_1—has been used. For every year between 2024 and 2028, the table includes a point projection, an upper confidence limit (UCL), and a lower confidence limit (LCL). Let's now discuss the importance of each part:

These represent the projected annual visitor arrival numbers. For instance, estimates for 2024 show that there would be 1,045,196.40 visitor visits; by 2025, that figure is expected to increase to 1,074,606.00. The increasing tendency is verified over time as the values rise, indicating a continual increase in visitor arrivals.

The highest calculation within the 95% confidence interval is indicated by this. It is the highest value that the model can forecast with 95% accuracy. For example, in 2024, UCL is expected to be 2,017,369.38, meaning that there is a 95% confidence level that actual tourist arrivals won't surpass this amount. The UCL varies significantly over time, indicating a growing lack of confidence in long-term factor predictions.

It represents the model's most optimistic estimate of a number with 95% certainty, which in this case is 2024 with an LCL of 475,321. It is the lower limit of the 95% confidence interval. With 95%

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probability, the number of arrivals is predicted to exceed 91,000 tourists. Similarly, LCL falls as UCL rises since uncertainty increases when projections are made for future dates.

The forecast for 2024:
1,045,196.40 is the estimated number of visitors to the region.
Projection with 95% Confidence: Upper Limit: 2,017,369.38; Lower Limit: 475,321.91
Forecast for 2028

The region is expected to get 1,156,987.09 tourists.
95% confidence level for the forecast is: Lower Limit: 179,546.91; Upper Limit: 4,062,926.89

The forecast indicates a steady growth in the number of visitors between 2024 and 2028, increasing by 30,000–40,000 per year.
The increases in the upper and lower confidence limits become more noticeable as we project further into the future. This demonstrates how challenging and erratic long-term projections are typically.
Furthermore, a wide range of values—from as low as 179,546.91 on the lower end to 4,062,926.89 on the upper end—are projected for the year 2028. This demonstrates that the number of tourists who come can be influenced by variables other than the tourists themselves, such as the state of the economy and geopolitical concerns. The model offers a generally optimistic outlook for upcoming visitor arrivals. However as the broader confidence intervals show, there is greater uncertainty associated with the temporal forecasts.

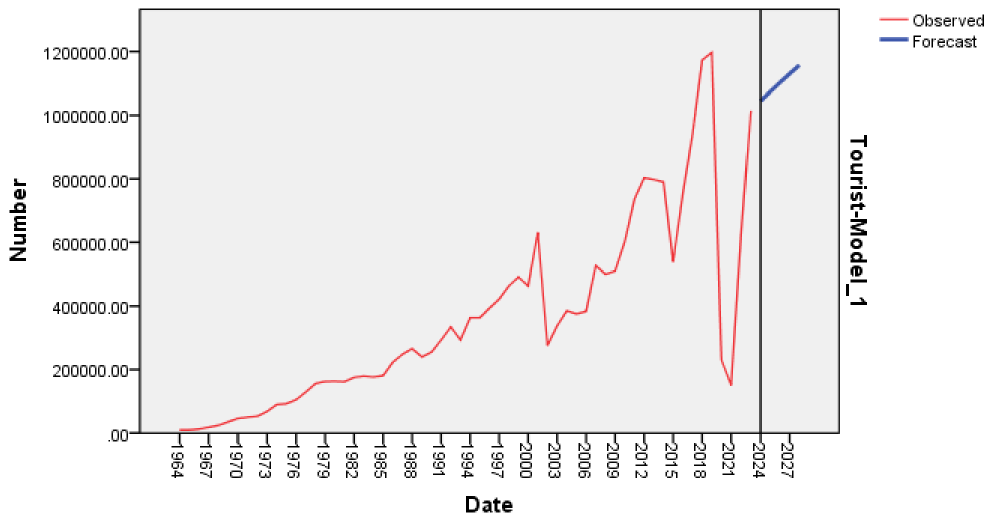

Figure No. 4

Discussion

The ARIMA model was utilized by the writers of this study to forecast the amount of foreign visitors that will visit Nepal between 2024 and 2028. The model results and empirical analysis of related studies show that the ARIMA is a reasonably reliable short-term forecasting technique that can successfully capture the seasonality and patterns in traveler demand. Its shortcomings, meanwhile, stem from the fact that it struggles to produce accurate long-range forecasts.

The study's findings are in line with those of Shrestha, Adhikari, Sapkota, and other researchers who have also demonstrated the effectiveness of the ARIMA model in explaining variations in the number

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of foreign visitors. For example, Shrestha's projections using ARIMA of the order of (1, 1, 1) for the years 2000 to 2020 were dependable and accurate, demonstrating the ARIMA's potency as a tool for tourism strategy planning. The forecasting skills of the model were explained by the research done by Subedi (2017) as well as Ghimire and Sharma (2020), particularly for seasonal time series and short-term forecasting.

This research strengthens the evidence. The tourism inflow prediction for the years 2024–2028 indicates a gradual increase in the number of visitors, with estimates of 1,045,196 in 2024 and 1,156,987 in 2028. The upward trend aligns with Nepal's tourist recovery from a prolonged period of worldwide disruption, and the forecasts are important for the examination of the sector's resources and overarching plans.

The ARIMA model is the best at managing short-term forecasts, but its inability to make long-term predictions is shown by the projections' expanding confidence ranges. For instance, there is a fairly wide range of opinions regarding the forecast for 2028, with an upper limit of 4,062,926 and a lower confidence limit of 179,546. This variation implies that ARIMA will not be useful for anything more than short-term projections, especially when considering external factors like the status of politics, the performance of the world economy, and even weather-related events.

Subedi (2019) has also gone to these lengths to demonstrate how external shocks, like hunger and political instability, that negatively impact tourist levels are not taken into account by the ARIMA model. Consistent with these claims, the present study presents analogous reasons regarding the growing disparities noted in forecasting outcomes at time horizons beyond which accurate forecasts are produced, such as 2028. Pradhan, B., & Koirala, S. (2024) have stressed this, describing how the varying results brought about by exogenous shocks might provide challenges for the ARIMA model in various economic situations.

The administration of tourism in Nepal is significantly impacted by the seasons. To effectively utilize the tourism resources at hand, Khatri et.al.(2024) contend that knowledge of seasonal variation is essential. This study's usage of the ARIMA technique effectively captures seasonal variation. This supports the expansion of tourism in a sustainable way by assisting industry participants and policymakers who want to predict visitor arrivals with seasonal variability factors included to plan for high and low seasons.

The ARIMA model is highly successful for managing tourism in Nepal because it can estimate the country's demand for short-haul travel following seasonal trend curves, as detailed in Upadhayaya, . (2021) study on tourism trends in South Asia. These findings are in line with the research and provide more evidence that ARIMA is a helpful tool for forecasting shorter periods, particularly in places like Nepal with distinct tourist seasons.

The R-squared, the Ljung-Box test, and run tests, among other methods, were used in this study to evaluate the statistical robustness of the ARIMA model. With a very high R-squared stationary value of 0.824, the model can explain 82.4% of the variability in the stationary series. This indicates that the model closely fits the time series data on the number of incoming tourists. Additionally, the Ljung-Box test results (p-value = 0.988) support the strong fit by indicating that the residuals are uncorrelated, implying that the model captures the timely pattern of the data without accounting for the variation in the series caused by strong autocorrelation. Since there are fewer outlier observations, the model is more likely to produce correct predictions because it was not apparent that there were any extremes that could have affected the forecasts.

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The research's conclusions have several implications for Nepal's tourism-related planning and strategies. The correct estimation of foreign visitor arrivals facilitates the formulation of well-informed decisions about resource allocation, infrastructure construction, and even promotional efforts. The higher-than-anticipated number of visitors should be a source of hope for Nepal's tourism industry as long as the appropriate policies are put in place to slow down the growth of the industry.
However, the narrowing of the confidence intervals suggests that long-term prediction is being done with less certainty. This suggests that flexible and adaptable tourist tactics are required. There are several implications for tourism planning and strategies in Nepal arising from the research findings. Accurate estimates of the number of foreign visitors allow for the creation of infrastructure, the distribution of resources, and even the creation of advertising campaigns. As long as the appropriate policies are put in place to slow the growth of tourism, the higher-than-anticipated number of visitor arrivals should be a cause for optimism and provide synergies for Nepal's tourism industry.
However, as the confidence intervals get smaller, it seems like longer-term predicting is being done with less certainty. This suggests that tourism strategy must be flexible and adaptable.

Conclusion

This study employed the ARIMA model to forecast the number of foreign visitors to Nepal between 2024 and 2028. It also examined the patterns in their arrivals and the model's suitability for these kinds of forecasts.

According to the ARIMA model analysis, there has been a steady increase in the number of foreign visitors to Nepal over the specified period. By the end of 2028, the number is expected to have increased to roughly 1156987 from 1045196 in 2024. This indicates the optimistic outlook for the tourist industry's revival and expansion, which will be primarily fueled by promotions, improved facilities, and the freedom for previously unable-to-travel individuals to do so.
According to the model validation requirements, the model matched the data quite well, as evidenced by its 0.824 model stationary R-squared score. As a result, the model can largely explain the variation in visitor arrivals. Further supporting the validity of the fitted model is the lack of a substantial auto correlogram on the residuals obtained from the Ljung-Box statistics. However, it is wise to exercise caution when making such long-term projections because the extent to which external factors affect tourism is becoming increasingly unknown.

Based on statistical criteria like R-squared and other error values, the ARIMA (1,0,0) model was out to be the most effective. It is especially advantageous for the stakeholders in tourism management when it consistently restores the visitor pattern trend.
In addition to its ability to produce predictions, the model also highlights certain difficulties. First, there should be a great deal of caution when making long-term projections because external factors like weather patterns, political unpredictability, and economic development or decrease could have a significant impact on actual arrivals. Therefore, it will be more accurate to place some caution on such projections even though some quite optimistic estimations have been made.
The findings of this study are highly pertinent to decision-makers, tourism industry participants, and local businesses. The anticipated growth can support the creation of policies, the allocation of resources, and the design of advertisements aimed at enhancing Nepal's tourism offeringsIn conclusion, the ARIMA model improves our understanding of the patterns in Nepal's tourism business by

accurately anticipating the trend of visitor arrivals. However, the findings emphasize the need of adaptable strategies to the circumstances and the necessity of ongoing observation of other factors that might influence the dynamics of tourism. Future research is advised to add more factors to the model to strengthen it and improve its predictive power, which will give Nepal's foreign tourism industry a more nuanced perspective.

Implication

When it comes to forecasting the quantity of tourists that will arrive in a short amount of time, the algorithm shows remarkable accuracy. However, as the distance from the present to the future increases, the forecast does not stay the same since the confidence intervals grow in size, indicating a rise in uncertainty.
Potential Growth: The prediction indicates a steady increase in the number of visitors between 2024 and 2028, providing short-term hope for the travel industry.
The higher mistakes associated with long-term projections of tourist arrivals are indicated by the progressively pronounced reinforcement of the upper (UCL) and lower (LCL) confidence bounds in such a scenario. In other words, adjustments to these variables could have a significant impact on the quantity of visitors that arrive.

Recommendations for Further Research

Examining External aspects: To enhance the model's capacity for long-term forecasting, future research may incorporate external aspects such as global events, sociopolitical developments, and the economy.
Exploring Non-Linear Models: Since uncertainty grows as one approaches the prediction horizon, non-linear models or non-linear hybrids (such as ARIMA with Neural Networks) may be used to analyze visitor arrivals.
Examine Seasonal Trends: In this instance, seasonal ARIMA models are probably going to be useful for predicting short-term fluctuations in tourism.
Data Granularity: By utilizing more stratified data, such as monthly or quarterly visitor arrivals, prediction accuracy can be enhanced and possible changes in tourist behavior can be identified.
Assessing Regional Influences: By including the geographical components of the prediction model and expanding its application to additional locations of Nepal that still permit the expansion of tourism, the model's overall performance will be enhanced.

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