FORECASTING SAUDI TOURISM DEMAND FOR VISION 2030: A COMPARATIVE ANALYSIS OF REGRESSION AND LSTM MODELS

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ABSTRACT

Tourism is central to Saudi Arabia's Vision 2030 diversification agenda. Reliable demand intelligence is needed to plan investment, capacity, and seasonally targeted interventions. Through substantial investments in infrastructure, heritage conservation, and digital transformation, Vision 2030 aims to position Saudi Arabia as a leading global tourism destination. Existing studies rarely integrate driver attribution with robust nonlinear forecasting, and often under-capture seasonal and pandemic shocks. To address this gap, we develop a dual-scope framework that (i) explains variation in total tourists using regression and (ii) forecasts future inflows with deep learning. The driver model examines tourist type, reason for visit, spending behavior, religious periods (e.g., Ramadan, Hajj), and pandemic effects. A degree-3 polynomial regression achieves the highest explanatory fit ($R^2 = 0.805$), with reason for visit and tourist type emerging as significant determinants. For forecasting, we design and compare several LSTM architectures; the best, a generator–discriminator LSTM, attains testing $R^2 = 0.756$, capturing nonlinear and seasonal structure. Together, these results unite driver evidence with accurate forecasts, supporting targeted marketing, resource allocation, and season-specific operations in line with Vision 2030. The study contributes an integrated dual-scope framework for Saudi arrivals, domain-specific exogenous design such as religious/pandemic, and comparative deep-learning benchmarks aligned to policy-relevant metrics moving beyond determinants-only studies, spending-centric ML/ARIMA, and attribution-free ensembles. By uniting interpretable driver evidence with accurate deep-learning forecasts under Vision 2030, this study offers decision-grade demand intelligence that the current literature has not yet provided in a single, Saudi-specific framework.

Keywords: *Machine Learning, Deep Learning, Regression Analysis, Long Short-Term Memory, Tourism Sector.*

1. INTRODUCTION

This chapter introduces the research presented in this thesis, which focuses on modeling and forecasting Saudi Arabia's tourism demand to enhance the tourism sector. Section 1.2 provides a brief overview of the tourism sector in Saudi Arabia, while Section 1.3 outlines the challenges facing Saudi tourism. Section 1.4 reviews previous studies conducted in Saudi Arabia, and Section 1.5 explains the study's aim and objectives.

1.1 Brief overview of the tourism sector in Saudi Arabia

Tourism plays a vital role in economic growth, cultural exchange, and social development worldwide. It significantly contributes to gross domestic product, generates employment opportunities, and drives infrastructure development [1]. Moreover, tourism fosters cultural understanding by enabling people to experience diverse traditions, languages, and lifestyles, thereby enhancing global unity and cooperation [2]. Given its wide-ranging impact, tourism remains a key driver of global progress and prosperity.

The tourism sector in Saudi Arabia has grown significantly as part of Vision 2030, which aims to diversify the country's economy by reducing dependence on oil revenues and expanding key sectors such as tourism. As part of this vision, substantial investments have been made to enhance tourism infrastructure, leading to the expansion of hotels, transportation networks, and restaurants. Additionally, new cultural and adventure tourism

destinations have been developed, attracting both domestic and international visitors. These efforts not only stimulate local businesses and generate employment opportunities but also showcase Saudi Arabia's rich heritage, natural landscapes, and modern attractions on the global stage. By 2030, the tourism sector is expected to be a major driver of economic diversification and sustainable development [3].
Meanwhile, the Saudi industry is experiencing exciting growth opportunities, particularly with the rapid development of Saudi Arabia's tourism infrastructure, including hotels, transportation, and attractions, to accommodate the increasing number of visitors.

To ensure smooth operations and optimal resource management, predictive analytics can play a vital role. By leveraging visitor flow statistics, hotel occupancy rates, and transit usage data, authorities can accurately forecast peak periods, optimize infrastructure development, refine pricing strategies, and enhance capacity management, ultimately improving the overall tourism experience [4].

A primary challenge is the shortage of skilled local professionals in the tourism and hospitality industries. As of mid-2024, only about 25.6% of tourism sector jobs were held by Saudi nationals, with expatriates comprising the majority of the workforce [5]. To address this, the government is investing in training programs aimed at preparing young Saudis for roles in tourism, culture, and sports, to create one million jobs by 2030 [1]. Furthermore, machine learning techniques can be utilized to analyze demand across different types of tourism domain, enabling the government to design specialized training programs tailored to various tourism domain and better prepare young Saudis for targeted workforce needs.

Saudi Arabia's tourism sector suffers from strong seasonality, with sharp peaks during Hajj and Ramadan and low tourist numbers during other times of the year [2]. This uneven distribution creates challenges like overcrowded infrastructure in peak seasons and underutilized facilities during off-peak periods, causing inefficient resource management [6].
To solve the seasonality problem, advanced time serice techniques can be applied to accurately forecast tourist flows by capturing complex seasonal patterns, religious events, and weather effects [7]. With precise forecasts, Saudi policymakers and businesses can optimize infrastructure planning, resource allocation, and marketing strategies, achieving stable tourism growth throughout the year [3].

1.2 Previous studies conducted in Saudi Arabia

There are studies have explored Saudi Arabia's tourism growth and forecasting, each offering valuable insights into different aspects of the sector. *Tourism Economics* evaluates the country's tourism potential through scenario forecasting, focusing on digital marketing strategies and infrastructure investments [8]. However, while it provides traditional forecasting models, it does not incorporate machine learning techniques that could enhance predictive adaptability to dynamic market changes.

Similarly*, Alanzi, (2023)* utilizes econometric models, such as the Gravity Model, to analyze economic and policy factors influencing inbound tourism. The study does not address modern drivers of tourism growth or integrate machine learning for more precise forecasts [9].

On the other hand, *Louati et al, (2024)* applies advanced machine learning techniques to classify spending behavior, and forecasting tourist spending using the traditional model ARIMA [10].
The study supports policymakers with tools for optimizing resource allocation and helps businesses enhance marketing strategies through targeted insights. Moreover, the study does not examine advanced machine learning techniques for forecasting and focuses solely on spending behavior without addressing tourism growth.

The selection of the core variables in this study is guided by both theoretical and contextual considerations. Tourism demand in Saudi Arabia is strongly influenced by factors such as travel motivations, tourist profiles, spending behavior, seasonal variations, religious periods, and global disruptions such as the COVID-19 pandemic. These variables capture key structural characteristics of tourism activity in the country and reflect both economic and cultural drivers of visitor flows. Moreover, the dual methodological framework combining regression analysis and deep learning forecasting was selected to address both explanatory and predictive aspects of tourism demand modeling.

These previous studies highlight the need for further research to explore the factors influencing tourism demand and to develop comprehensive forecasting

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approaches that enhance predictive accuracy and adaptability within Saudi Arabia's evolving tourism landscape.

- First, such research supports infrastructure and resource optimization by identifying key demand drivers such as reasons for visiting, tourist types, and time-based effects like seasonality or religious periods enabling planners to align hotel, transport, and service capacities with expected visitor flows.
- Second, it contributes to workforce development by helping decision-makers forecast which types of tourism are likely to grow, allowing for the creation of targeted training programs for Saudi nationals.
- Third, by understanding how tourism demand fluctuates due to seasonality, religious events, and visitor motivations, policymakers can design strategies to distribute demand more evenly throughout the year, ultimately improving both operational efficiency and the overall tourism experience.

1.3 Problem Statement

Based on the preceding discussion, several key research gaps emerge that motivate this study.

- Vision 2030 raises the forecasting bar: Saudi Arabia surpassed the 100-million visitor milestone and targets 150 million by 2030, requiring reliable, decision-grade demand intelligence for capacity, workforce, and policy planning.
- Prior Saudi studies are partial econometric determinants without adaptive ML forecasting, ML focused on spending/ARIMA rather than arrivals with deep learning, and high-fit ensembles without driver attribution or explicit religious/pandemic features in a unified framework.

1.4 Research Questions

Following research questions are proposed in this study:

- RQ1: Which factors such as tourist type, reason for visit, spending, religious periods, and pandemic effects significantly influence total tourist volumes in Saudi Arabia?
- RQ2: Can a parsimonious nonlinear regression (e.g., polynomial terms) deliver reliable out-of-sample predictions while retaining interpretability for policy use?
- RQ3: Do LSTM architecture improve forecast accuracy over classical baselines by capturing nonlinear and seasonal dynamics typical of tourism time series?
- RQ4: What incremental accuracy is gained by explicitly encoding religious periods and pandemic indicators versus models that omit these domain-specific signals?

Based on a review of studies published in Saudi Arabia, there is a noticeable lack of research that leverages advanced machine learning techniques to analyze the influencing factors on tourism and to forecast the tourism demand. Given the growing importance of the tourism sector under Vision 2030, there is an urgent need for data-driven insights to help stakeholders navigate uncertainties, optimize decision-making, and promote sustainable tourism development through innovative analytical approaches.

This research employs a two-Scope Approach:

- ○ Leveraging a regression model to analyze tourism trends and forecast future tourist numbers by studying the influencing factors, such as tourist types, reasons for visiting, tourist spending, season of weather, religious time, and pandemic times.
    - Do these factors significantly affect tourist numbers?
    - Can these variables be used to build a reliable regression model for predicting tourism demand?
- ○ Applying an advanced time series model, Long Short-Term Memory (LSTM), to forecast future tourism demand based on historical trends.

2 LITERATURE REVIEW

The main aim of this section is to review previous studies on modeling and forecasting tourism demand, as well as the significance of the tourism sector in Saudi Arabia. The chapter is structured as follows: Section 2.2 provides an overview of tourism in Saudi Arabia. Section 2.3 reviews global studies on modeling and forecasting tourism demand. Section 2.4 reviews local studies on the same topic. Finally, Section 2.5 presents the chapter's conclusion.

Tourism is a vital driver of economic growth, generating income, creating jobs, and fostering

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regional development through investments in infrastructure and services. It significantly contributes to foreign exchange earnings, helping to balance trade deficits and stabilize national economies. The sector enhances employment opportunities, both directly in hospitality and indirectly in supporting industries such as transportation and retail. Despite challenges like seasonality and environmental concerns, tourism remains a resilient industry, capable of sustaining economic activity even during downturns. Its role in promoting cultural exchange and global connectivity further strengthens its importance as a key pillar of sustainable development [11].

As tourism significantly impacts a country's economy. *García et al, (2024)* examined the relationship between tourism and economic development across 123 countries from 1995 to 2019 using the Dumitrescu and Hurlin adaptation of the Granger causality test. Their study challenges the conventional belief that tourism universally drives economic growth, demonstrating that the relationship depends on a country's level of development and tourism specialization [12]. The findings reveal that in countries with low levels of tourism specialization and economic development, tourism contributes to economic growth, suggesting that investments in tourism infrastructure and promotion can enhance development. Conversely, in highly developed countries with strong tourism sectors, the relationship is reversed economic development fosters tourism growth. This indicates that factors such as infrastructure, security, healthcare, and education play a crucial role in attracting more tourists to these destinations. Ultimately, policymakers in less developed nations should prioritize investments in tourism to stimulate economic growth, while developed countries should focus on maintaining and enhancing their socio-economic infrastructure to sustain their tourism sectors.

In Saudi Arabia the tourism sector has grown significantly as part of Vision 2030. Vision 2030 represents a transformative strategy aimed at reducing the country's reliance on oil revenues by diversifying its economy, with tourism playing a central role in this shift. As part of this initiative, the government has prioritized the expansion of tourism infrastructure, including hotels, transportation, and hospitality services, while also developing cultural and adventure tourism destinations. These efforts reflect a comprehensive commitment to fostering economic sustainability and enhancing the Kingdom's global competitiveness [13] .

Pratiwi & Muslikhat (2024) examine the role of Saudi Vision 2030 in transforming Saudi Arabia's tourism sector and how the government is implementing policies to diversify the economy through tourism [13]. They highlight the policy reforms implemented, such as easing visa restrictions and relaxing social regulations to attract international tourists. Additionally, they identify the significant investments in mega tourism projects like NEOM, The Red Sea Project, (Amaala, AlUla, Qiddiya, and Diriyah Gate), which aim to diversify tourism beyond religious visits. that will assist to achieve the goal for the tourism sector to contribute 10% of GDP and attract 100 million tourists annually by 2030, positioning Saudi Arabia as a competitive player in the global tourism industry. Forecasting the number of visitors and studying the factors that could affect tourism is essential for effective tourism planning and development. Accurate predictions enable policymakers to allocate resources efficiently, optimize infrastructure investments, and enhance tourism services to accommodate future demand.

2.1 The Role Of Traditional And Machine Learning Approaches In Forecasting Global Tourist Growth

Tourism needs to be forecasted using Artificial Intelligence AI by analyzing large datasets, including past visitor trends, economic indicators, social media activity, and real-time travel patterns, to generate accurate predictions. This enables policymakers to optimize infrastructure, resources, and marketing strategies for a more sustainable and efficient tourism industry [14].

This section reviews previous global studies on traditional and machine learning models for forecasting tourism demand and analyzing the impact of various factors on tourist demand for Saudi Arabian visits.

2.2 Traditional Time Series

Autoregressive Integrated Moving Average (ARIMA) is one of the traditional time series applications used for forecasting future values based on past data patterns. *Petrevska, (2017)* studied the Predicting Tourism Demand by ARIMA Models. The study aims to analyze and forecasting international tourism demand in North Macedonia using time series models [15]. The author applies and compares two different Autoregressive Integrated Moving Average (ARIMA) configurations, to identify the most suitable model for short-term forecasting and provide insights for policymakers in the tourism sector. The configuration is based on the parameters in the ARIMA (p, d, q) model which consists of three key parameters: p (autoregressive order), d (differencing order), and q (moving average order), which help capture patterns in time-series data. In the study, two configurations, ARIMA (1,1,1) and ARIMA (2,1,2), were tested to forecast international tourism demand. The ARIMA (1,1,1) model includes one lagged value (p=1) to predict the future, applies first-order differencing (d=1) to ensure stationarity, and incorporates one past forecast error (q=1) to refine predictions. Meanwhile, the ARIMA (2,1,2) model considers two past values (p=2) and two previous forecast errors (q=2) to improve accuracy.

The data was sourced from the State Statistical Office of North Macedonia and covered annual international tourist arrivals from 1956 to 2013. Before applying the models, the dataset was pre-processed to ensure stationarity through differencing, as initial tests indicated the presence of non-stationarity in the time series.

The study tested multiple ARIMA configurations and identified ARIMA (1,1,1) as the best-performing model for forecasting future tourist arrivals. The model predicted a 13.9% increase in international tourist arrivals by 2018, estimating a total of 455,107 foreign tourists, compared to 399,448 in 2013. An alternative model, ARIMA (2,1,2), projected a slightly lower increase of 9.9%, forecasting 439,247 tourists in 2018. To evaluate accuracy, the study applied Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Theil Inequality Coefficient (TIC). The MAPE for ARIMA (1,1,1) was 12.63%, compared to 14.51% for ARIMA (2,1,2), indicating that the former model produced more reliable forecasts. Similarly, the RMSE for ARIMA (1,1,1) was 49,426, slightly higher than 49,395 for ARIMA (2,1,2), while both models had similar TIC values around 0.068, suggesting comparable overall performance. The findings confirmed that ARIMA (1,1,1) provided a better balance between accuracy and simplicity, making it the preferred model for short-term tourism demand forecasting.

The study faced several limitations: firstly, it did not explore alternative forecasting techniques such as neural networks or hybrid models, which could potentially improve predictive performance. Additionally, the model did not incorporate external economic or policy-driven variables, such as GDP, exchange rates, or tourism promotion efforts, which might influence tourism demand. Furthermore, the study relied solely on annual data, limiting the ability to capture seasonal and short-term fluctuations that are often critical in tourism forecasting.

By comparing two time-series forecasting models, *Lin, (2023)* analyzed and predicted future trends in key sectors of the U.S. tourism industry, including airlines, hotels, car rentals, and travel agencies [16]. By applying and comparing Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing State Space (ETS). The study aimed to identify the most suitable model and provide insights for industry decision makers. The data was sourced from the St. Louis Federal Reserve (FRED) and pre-processed to account for long-term trends and seasonal variations before model application.

The Exponential Smoothing State Space (ETS) model, which assumes additive errors and no trend or seasonality, was found to be suitable for short-term predictions with stable data patterns. The ETS model performed more accurately for Revenue Passenger Miles, the Producer Price Index for Travel Agencies, and Passenger Car Rentals. Meanwhile, the ARIMA model required stationarity transformation through differencing before applying optimized ARIMA (p, d, q) configurations for each dataset. Specifically, ARIMA (1,1,1) (2,0,0) was found to be more accurate for Load Factor, while ARIMA (0,1,0) was the best fit for Exports of Services – Travel. The accuracy evaluation indicated that ARIMA models aligned more closely with volatile datasets, whereas ETS models generated stable and predictable outputs.

Despite its contributions, the study faced several limitations. It did not explore alternative forecasting techniques such as neural networks or hybrid models, which could potentially enhance predictive accuracy. Additionally, external economic and policy-driven variables were not incorporated, potentially affecting model robustness.

Seasonal Autoregressive Integrated Moving Average (SARIMA) and Long Short-Term Memory (LSTM) models are widely used in time-series forecasting (Shariff, 2022). *Wu et al. (2021)* conducted a study on Forecasting Tourist Daily Arrivals with a Hybrid SARIMA-LSTM Approach, aiming to improve the accuracy of short-term tourism demand predictions in Macau SAR, China. The study focuses on overcoming the limitations of traditional forecasting methods by integrating SARIMA, a linear statistical model, with LSTM, a deep learning-based nonlinear model.

The SARIMA model is an extension of the Autoregressive Integrated Moving Average (ARIMA) model that incorporates seasonality. It consists of three key parameters (p, d, q) for the non-seasonal component and three additional parameters (P, D, Q) for the seasonal component that means P (Seasonal Autoregressive order), D (Seasonal Differencing order), and Q (Seasonal Moving Average order). The LSTM model, on the other hand, is a recurrent neural network (RNN) capable of capturing long-term dependencies in time series data. The hybrid SARIMA and LSTM approach leverages the strengths of both models by first using SARIMA to extract linear trends and seasonal components and then applying LSTM to capture residual nonlinear patterns.

The study uses daily tourist arrival data from six different countries and regions covering the period from January 1, 2017, to April 30, 2019, consisting of 850 daily observations. The dataset was pre-processed to remove noise and ensure stationarity. The training data was used to fit the SARIMA model, which performed one-step rolling forecasts. The residuals from the SARIMA predictions were then fed into the LSTM model to improve forecasting accuracy.

The study tested multiple forecasting models on the six different countries and regions, including Naive Bayes-1, Seasonal Naïve, ARIMA, SARIMA, and LSTM, and compared them against the hybrid SARIMA-LSTM model. The SARIMA-LSTM model achieved the lowest RMSE and MAPE values across all six regions, demonstrating superior predictive performance compared to standalone models. The Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used as evaluation metrics to compare the models.

Despite its success, study has several limitations. Firstly, it relies on only two years of data, which may not fully capture long-term trends or external shocks, such as economic downturns or global crises. Additionally, the model does not incorporate external variables such as weather conditions, economic indicators, or policy changes, which could enhance forecasting accuracy.

2.3 Machine Learning for advanced time series forecasting

Long Short-Term Memory (LSTM) is an advanced time series application that is a type of recurrent neural network (RNN) designed to handle sequential data and capture long-term dependencies, and it is particularly useful for time series forecasting. Salamanis et al. (2022) explored the effectiveness of Long Short-Term Memory advanced time series application in improving long-term forecasting accuracy by incorporating exogenous variables such as weather data [17]. Using daily room reservation records from three hotels in Greece spanning multiple years, the study aimed to enhance hotel management's ability to predict future demand. The data was structured into time-series format, allowing the model to capture seasonal and long-term patterns.

The study implemented two main LSTM-based models:

- **LSTMB Model**: Trained solely in historical hotel booking data.
- **LSTMX Model**: Incorporated both historical booking data and weather variables (e.g., temperature, atmospheric pressure, humidity).

The models were optimized using the Root Mean Square Propagation (RMSProp) algorithm, and the architecture was tuned via a grid search method to determine the optimal number of LSTM layers and units for each hotel dataset. For evaluation the model the study used Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) metrics revealed that the LSTMX model outperformed both the LSTMB model and traditional statistical models, including ARIMA, Support Vector Regression (SVR), and Holt-Winters exponential smoothing. The RMSE values were consistently lower in the LSTMX model, confirming its robustness in capturing demand fluctuations. Despite its success, the study had limitations such as only weather variables were used as exogenous inputs, whereas macroeconomic factors, social media trends, or special events could further enhance predictive accuracy. Lastly, the model's effectiveness in longer-term forecasts (beyond seasonal horizons) remains unexplored, suggesting the need for future research incorporating hybrid modeling techniques or ensemble learning approaches.

Long Short-Term Memory (LSTM) was combined with another model. *Yu & Chen, (2022)* studied the improvement of tourism demand forecasting by leveraging deep learning techniques, particularly Long Short-Term Memory (LSTM) networks and Stacked Autoencoders (SAE) (18). Using monthly search engine trend data and tourist volume from a specific city over the period from 2014 to 2019, they pre-processed the data and transformed it into a time-series format.

The model construction involved two main stages. In the first stage, Pretraining Stage**,** LSTM-based autoencoders were stacked to learn feature

representations from the input data, enhancing the model's ability to capture long-term dependencies in time-series forecasting. In the second stage, Fine-Tuning Stage, the pre-trained layers were combined with an additional output layer to optimize forecasting performance by refining the learned representations. The traditional random weight initialization method was replaced with a hierarchical greedy pre-training approach, improving the model's effectiveness.
The study tested models with 1, 2, 3, 4, and 5 hidden layers, and it was found that using more than two hidden layers led to significantly higher errors. By using the evaluation metrics demonstrated that the two-layer SAE-LSTM model achieved a lower Mean Absolute Percentage Error (MAPE) of 3.125 compared to other configurations, confirming its superior performance. Additionally, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were consistently lower for the SAE-LSTM model than for the standard LSTM, reducing overfitting and improving generalization. The results validated that incorporating stacked autoencoders in the pretraining stage enhances tourism demand predictions by replacing random weight initialization with hierarchical feature learning. However, the study faced limitations in implementing the model due to its narrow geographic focus and the exclusion of macroeconomic factors, which may hinder its applicability in diverse settings.

In utilizing AI-driven for tourism forecasting, *De Jesus & Samonte (2023)* examined the predictive capability of Artificial Neural Networks (ANN) in forecasting tourist arrivals in the Philippines from 2008 to 2022 [19]. The study aimed to assess the effectiveness of ANN models trained with different data compositions and provide insights into optimizing predictive accuracy. The dataset was sourced from the Department of Tourism and related government agencies, covering monthly inbound tourist arrivals. Preprocessing steps included feature extraction and time-series analysis. The methodology that he followed utilized an Artificial Neural Network (ANN) model based on a Multi-Layer Perceptron (MLP) architecture for time-series forecasting and employed the Autoregressive (AR) model, which used lagged values for predicting future tourist arrivals. The training step was by segmenting the training dataset into three compositions based on key COVID-19 periods, which are:

- **Data Composition1:** January 2008 – January 2020 (before the first confirmed COVID-19 case in the Philippines)
- **Data Composition 2:** January 2008 – March 2020 (before the suspension of tourist arrivals)
- **Data Composition 3:** January 2008 – December 2020 (including the period when entry restrictions were imposed due to the new COVID-19 strain)

The best-performing model was trained with data that included the pandemic period, achieving an R^2 of 0.926 and a MAPE of 13.9%, indicating a high degree of accuracy. The results demonstrated that incorporating data from unexpected events enhanced the model's learning process and predictive performance. Considering all of this, external factors like economic indicators and traveler sentiment were not included, potentially affecting prediction robustness.

Núñez et al. (2024) conducted a systematic review of machine learning applications in tourism, analyzing various ML models used for forecasting, recommendation systems, and sentiment analysis {4]. The author aimed to evaluate the effectiveness of ML techniques performed in real-world tourism applications and address the key challenges within the tourism sector, such as demand prediction and customer segmentation.
The dataset included diverse sources such as online travel reviews from TripAdvisor and Yelp, social media data from platforms like Twitter and Instagram, and structured data from booking systems and geospatial services. The preprocessing phase involved feature extraction, sentiment analysis, and time-series transformations to optimize model performance. This methodology included an extensive comparison of multiple machines learning approaches, highlighting the dominance of supervised learning techniques, particularly Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM). Reinforcement learning and hybrid ML techniques were also explored for complex decision-making processes in tourism forecasting. The study examined the application of deep learning architectures, such as Long Short-Term Memory (LSTM) networks for time-series forecasting and Random Forests for predictive analytics. The study reported that deep learning models, particularly CNNs and LSTMs, demonstrated superior predictive accuracy in various tourism-related tasks. Neural Networks (CNN & ANN) accounted for 15% of ML applications in

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tourism, showing strong forecasting capabilities. The Random Forest algorithm, widely used for tourist demand forecasting, exhibited high predictive accuracy. A comparative analysis between Reinforcement Learning, Random Forest, and Multinomial Logit models revealed that Reinforcement Learning achieved the highest accuracy, followed by Random Forest, while the Multinomial Logit model performed the weakest in terms of prediction reliability.

Despite these advancements, the study acknowledged several limitations. One major drawback was the challenge of integrating fragmented datasets from multiple sources, which complicated data harmonization. Additionally, while the study demonstrated the effectiveness of ML in tourism forecasting, it did not extensively compare the performance of emerging techniques like quantum computing or AutoML. The study also noted that many ML models lacked real-time adaptability and scalability, making it difficult to apply them effectively in dynamic tourism environments.

2.4 The Role Of Traditional And Machine Learning Approaches In Forecasting Tourist Growth Globally.

Accurate forecasting of tourist growth at the local level is crucial for optimizing resources, infrastructure, and marketing strategies. Reliable predictions of visitor numbers, seasonal demand, and tourism trends are essential for effective planning and decision-making. Policymakers depend on data-driven insights to allocate resources efficiently, enhance infrastructure, and develop sustainable tourism strategies aligned with national goals.

However, research on machine learning-based forecasting of tourism demand in Saudi Arabia remains limited. This lack of accessibility may hinder international researchers and policymakers from gaining comprehensive insights into the country's tourism sector. This section examines both traditional and machine learning-based forecasting methods, comparing their strengths and limitations in predicting tourist growth in Saudi Arabia.

Alanzi (2023) studied the modeling and forecasting Saudi Arabia's inbound tourism demand by investigated the factors influencing international tourist arrivals and developed forecasting models to predict tourism demand by purpose of visit [9]. The study aims to assess the impact of economic and non-economic determinants on inbound tourism and evaluate the forecasting accuracy of different econometric and time-series models. The methodology utilized both econometric and time-series forecasting techniques. The econometric approach included the Autoregressive Distributed Lag (ARDL) model, the Error Correction Model (ECM), and the Vector Autoregression (VAR) model. The time-series approach employed ARIMA, naïve forecasting, and exponential smoothing methods. Additionally, the study explored combination forecasting using Simple Average (SA) and Variance–Covariance (VACO) methods to enhance prediction accuracy.

The dataset included international financial institutions, Saudi tourism authorities, and global development databases. to extract the panel of data covering 21 origin countries influencing Saudi Arabia's religious inbound tourism demand spanning the years 2000 to 2019, incorporated various variables divided into two categories: Economic Factors, including Gross Domestic Product (GDP), Exchange Rates, Travel Costs, Cost of Living, Foreign Direct Investment (FDI), and Trade Openness; and Non-Economic Factors, such as Political Risk, the Human Rights Index, Global Health Risks, Relative Temperature, the Destination Prosperity Index (Legatum Prosperity Index), Visa Restrictions, Word-of-Mouth Effects, Saudi Students Studying Abroad, and the Number of Expatriate Workers in Saudi Arabia.

The results demonstrated that time-series models outperformed econometric models in 83% of cases, with the exponential smoothing model achieving the best accuracy for religious tourism (RMSE = 0.028, MAPE = 16.818%) and the naïve approach performing best for visiting friends and relatives (VFR) tourism (RMSE = 0.062, MAPE = 26.652%). Combination forecasting produced more accurate predictions in 66% of cases compared to individual model forecasts. These findings underscored the importance of selecting appropriate forecasting methods based on the type of tourism demand.

Despite the positive results presented in the paper, several limitations exist. For example, non-economic factors such as visa policies and climate change were not extensively analyzed, leaving potential gaps in understanding tourism determinants. Additionally, while the study disaggregated tourism demand into religious, business, and VFR segments, further segmentation could provide deeper insights. The research relied on traditional econometric and time-series approaches but did not incorporate advanced artificial intelligence techniques like neural networks, which

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have shown promise in improving predictive accuracy.

Another study proposed by *Louati et al (2024)* which uses Autoregressive Integrated Moving Average (ARIMA) to forecast the spending behaviors of tourists and used machine learning models to classify tourist spending behaviors into three distinct classes: Low Spenders, Moderate Spenders, and High Spenders. It aimed to assess how machine learning techniques could optimize forecasting accuracy and support sustainable tourism development. The dataset was sourced from the Saudi Tourism Authority, covering tourism data from 2015 to 2021, including the number of tourist visits, overnight stays, and total expenditure. Data preprocessing involved handling missing values, translating from Arabic to English, and normalizing for consistency. Exploratory Data Analysis (EDA) was conducted to identify spending patterns across different regions and time periods.

The methodology utilized multiple ML models, including Decision Trees, Random Forests, K-Neighbors Classifier, Gaussian Naive Bayes (GNB), and Support Vector Classification (SVC) for classifying spending behaviors. Additionally, the ARIMA model was employed for time-series forecasting to predict the economic landscape of Saudi Arabian tourism from 2022 to 2030. Hyperparameter tuning techniques such as Grid Search, Gradient Descent, and model-specific parameter optimization were applied to enhance predictive performance.

The best-performing model was the Gaussian Naive Bayes (GNB) classifier, achieving an accuracy of 99.99%, significantly outperforming the Decision Tree model, which had an accuracy of 76.56%. The ARIMA model forecasted a decline in tourism expenditure due to the COVID-19 pandemic, followed by a gradual recovery from 2022 onwards. The study's predictive insights aligned with Saudi Vision 2030's objectives, demonstrating the potential of AI-driven approaches in tourism planning and policymaking.

The dataset was limited to 2015–2021, restricting real-time validation post-pandemic. The exceptionally high accuracy of the Gaussian Naive Bayes model suggests possible overfitting, raising concerns about its generalizability to unseen data. Furthermore, the research did not compare deep learning models such as LSTM or Transformer-based architecture, which could provide a more robust approach for long-term forecasting.

With the advancement of deep learning and its growing application in forecasting *Alarfaj and Alghowinem (2019)* compare three forecasting models to study the forecasting air travel demand for Saudi Arabia's low-cost carriers (LCCs) [20]. The aim was to assess the impact of economic determinants and seasonal variations (such as Islamic holidays Hajj and Ramadan) on low-cost carriers' passenger demand and evaluate the accuracy of different forecasting techniques. The dataset was obtained from King Khalid International Airport, covering domestic flight records from 2009 to 2017, and included variables such as population size, GDP, employment rate, per capita income, economic growth rate, and jet fuel prices. The preprocessing of data involved z-score normalization to standardize variables.

The methodology utilized three forecasting model techniques. The statistical approach included Multiple Linear Regression (MLR) as a baseline model, while the machine learning approach employed Artificial Neural Networks (ANN) and Genetic Algorithms (GA). GA is a method for solving both constrained and unconstrained optimization problems that are based on natural selection, the process that drives biological evolution.

The model evaluation was conducted using the Mean Absolute Percentage Error (MAPE) to compare forecasting accuracy.

The results demonstrated that artificial intelligence models outperformed traditional regression techniques, with Genetic Algorithms achieving the best forecasting accuracy, followed by ANN, while MLR showed the weakest performance. These findings highlighted the effectiveness of AI-driven forecasting methods in capturing complex demand patterns in Saudi Arabia's low-cost carrier's market.

The dataset focused exclusively on domestic passenger demand, omitting international low-cost carrier traffic, which could provide a more comprehensive analysis. While Islamic holidays were considered, other seasonal variations such as school vacations and summer travel were not extensively analyzed. The analysis was conducted at a monthly level, but higher granularity (e.g., weekly or daily forecasts) could enhance prediction accuracy. Additionally, the study compared models individually but did not explore ensemble techniques that combine multiple forecasting approaches for improved results.

Saudi tourism research often separates determinant analysis from modern nonlinear forecasting methods and tends to underrepresent Saudi-specific calendar effects and pandemic regime changes. Therefore, this study selects core factors that are both policy-relevant and structurally significant for Saudi tourism demand and evaluates them within a dual-scope framework combining explanatory regression and deep learning forecasting models.

Lee et al (2025) demonstrated Macro/global tourism-demand drivers and classical forecasting baselines [21}. This research also identifies macro determinants of arrivals (income, prices, exchange rates, accessibility) and generate baseline forecasts using classical econometric/time-series models. This research employs nonlinear regression (polynomial terms), encodes Ramadan/Hajj and COVID shocks, and benchmarks against classical SARIMA/ETS to demonstrate forecasting improvements. The Saudi Ministry of Tourism argues that Saudi-focused econometric inbound tourism studies Inbound arrivals by purpose or origin markets (Saudi context) are discussed [22]. Limited machine/deep learning use; weak handling of nonlinearities; calendar/religious effects sometimes under-modeled; forecasting rarely benchmarked against modern ML Ensure religious calendar is treated as a first-class driver; include pandemic effects and structural breaks. A Dual-scope framework is recommended with an: interpretable driver model + deep learning forecasts; explicit Ramadan/Hajj indicators and COVID regime encoding.

Louati, A et al., (2024), employs the Spending-centric ML in Saudi tourism. Tourist expenditure / spending classes; business analytics [10] Classifiers (DT/RF/SVM/GNB); ARIMA for spending are all examined. Focus on spending rather than arrivals; arrivals forecasting often remains classical (ARIMA); limited deep learning comparison; risk of overfitting with very high accuracy claims. If spending variables are used, justify them as composition proxies and test their predictive contribution to arrivals Among the other recommendations are that spending variables are used as explanatory/compositional drivers (with caveats); keep arrivals as the main forecasting target; benchmark deep learning architectures. Hybrid models are proposed and SARIMA + LSTM residual modeling. Apply LSTM variants with exogenous encodings; compare architectures and integrate Saudi-specific calendar structures.

Waciko et al., (2025) investigates Ensemble / tree-based ML forecasting [24]. The variables examined are Tourism arrivals forecasting XGBoost, LightGBM, Random Forest with lag features, stacking ensembles. Limited interpretability: domain calendar factors sometimes under-emphasized according to the authors. Recommendations include ensuring calendar and shock variables are included and test their contribution. Implement feature ablation tests (with/without Ramadan, Hajj, COVID) to justify "core" explanatory factors.

Saudi Tourism Authority (2026) examined the Vision 2030 / Saudi tourism policy literature, and also sectoral strategies, mega-projects, tourism targets [6]. Policy analysis: scenario projections are discussed. These are rarely linked quantitatively to tourism demand drivers; forecasting rigor often limited Select drivers linked to policy levels (visa policy, accessibility, events, mega-projects). Position selected factors as policy-relevant explanatory variables supporting tourism planning and operational decisions
Tourism is a key driver of economic growth, cultural exchange, and job creation, contributing to sustainable development and global connectivity.
The studies published on the use of machine learning for forecasting tourist demand in Saudi Arabia remain relatively limited. Notably, no study has examined the growth of tourism in Saudi Arabia using Long Short-Term Memory (LSTM), which is known for its superior predictive capabilities. Additionally, studying the factors influencing tourism, along with the impact of Vision 2030, is essential for a comprehensive understanding of tourism growth in the country.
This research aims to further investigate predictive analytics models in the tourism sector by utilizing an advanced time series model, Long Short-Term Memory (LSTM). Also, it seeks to analyze tourism trends and forecast future tourist numbers and revenue based on key factors such as tourist types, reasons for visiting, lengths of stay, and developments in the tourism sector. These developments, aligned with Vision 2030, include initiatives such as creating new festivals and preserving historic cities to enhance Saudi Arabia's appeal as a global tourism destination.

3 METHODS AND MATERIALS

3.1 Introduction

This research employs a two-scope approach to assess the impact of Vision 2030 on tourism and forecast future tourist growth in Saudi Arabia

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This chapter aims to present the dataset, and the methodology employed in this research. It is structured as follows: Section 3.2 provides an overview of the dataset used in the study. Section 3.3 discusses the preprocessing techniques applied to the data. Finally, Section 3.4 introduces the models utilized in this research.

The dataset was extracted from the Data Saudi, which collaborates with the Ministry of Economy and Planning, which collects data from the Ministry of Tourism and the Saudi Central Bank. The duration of the collection of the dataset from 2015 to 2023 on a monthly basis *Ministry of Economy & Planning, (2025)* [26].

Three datasets have been extracted as follows:

- Two datasets report the total tourist by reason for travel, categorized by traveler type (domestic and inbound). Each set contains 540 rows with the following columns:
  - Date.
  - Reason of visting.
  - Type of tourist.
  - Total Tourist.

Table 1 shows the domestic dataset.

Table 1. Example of Domestic Dataset.

الشهر	غرض الزيارة	فئة السائح	عدد السياح
2015-01	الأغراض الدينية	السياحة المحلية	1194.96762
2015-01	الترفيه	السياحة المحلية	1854.26676
2015-01	الأعمال	السياحة المحلية	169.023621
2015-01	زيارة الأصدقاء أو الأقارب	السياحة المحلية	1380.92465
2015-01	أخرى	السياحة المحلية	224.151901

Table 2 Shows The Inbound Dataset.

الشهر	غرض الزيارة	فئة السائح	عدد السياح
2015-01	الأغراض الدينية	السياحة الوافدة	1188.680957
2015-01	الترفيه	السياحة الوافدة	269.83045
2015-01	الأعمال	السياحة الوافدة	21.93278138
2015-01	زيارة الأصدقاء أو الأقارب	السياحة الوافدة	476.2860098
2015-01	أخرى	السياحة الوافدة	290.3785186

- The third dataset focuses on reporting on the spending behavior of travelers based on their type (domestic, inbound). The set contains 216 rows with the following columns:
  - Date.
  - Tourism type.
  - Spending values.

Table 3 Shows The Spending Dataset.

الشهر	فئة السائح	معدل الإنفاق للرحلة الواحدة
2015--01	السياحة الوافدة	3,979.73
2015--01	السياحة المحلية	908.33

3.2 Preprocessing

Before using the dataset, several data preprocessing techniques are necessary to clean, structure, and transform the data. Below are the essential steps:

3.2.1 Combine the datasets.

In this section we will combine the three datasets to produce one final dataset to start our analysis.

- Union the domestic and inbound datasets to form a consolidated view of tourism volume by reason and type.
- Then merged the union tourism dataset with the spending dataset based on the Date and Tourism type.
- The final dataset has 1080 rows and five features as is shown in Table 4.

Table 4. Example Of The Dataset.

MONTH	VISITING_REASONS	TOURIST_TYPES	TOTAL_TOURISM	SPENDING
01/01/2015	الأغراض الدينية	السياحة المحلية	1,194.97	225.04
01/01/2015	الترفيه	السياحة المحلية	1,854.27	349.20
01/01/2015	الأعمال	السياحة المحلية	169.02	31.83
01/01/2015	زيارة الأصدقاء أو الأقارب	السياحة المحلية	1,380.92	260.06
01/01/2015	أخرى	السياحة المحلية	224.15	42.21

3.2.2 Handling Inconsistencies.

- Standardize column names and the values of columns, to ensure consistent naming from Arabic to English.
- After joining the datasets, spending values were aggregated based on date and tourism type. To resolve this and allocate spending by travel reason, the total spending for each travel reason was proportionally distributed according to the percentage share of each visiting reason within that tourism type.

3.2.3 Data Transformation

- **Convert Data Types**

Convert dates (years, months) into datetime format.

- **Transformation**
  Normalize the continues variable spending by using Standard Scaler technique to transfer the values from 0 to 1 to have a mean of zero and a standard deviation of one, ensuring that features with large magnitudes do not dominate the learning process *Kuhn et al (2013).*

- **Feature Engineering**
  - Created variables to identify the season of the year.
  - winter: from December to February.
  - Spring: from March to May.
  - Summer: from June to August.
  - Autumn: from September to November.
  - Created variables to represent religious periods in Saudi Arabia, which are Ramadan and Hajj by Hijri month**.**
  - Created variables to represent the pandemic period (during COVID-19 starting from April in 2020 till May in 2021).

3.2.4 Encoding categorical variables.

Encode categorical columns such as reason of visiting, tourism type, and season of the year.

3.2.5 Additional pre-plong- and short-termand short term memory

The dataset was restructured into a monthly-based format using a pivot table transformation, resulting in 108 rows, to prepare the data for LSTM model training and evaluation.

3.3 Models

A Two-Scope Approach will be employed in this research, integrating Regression Analysis and Long-Short-Term Memory (LSTM) models. These models have been selected to provide a comprehensive understanding of tourism trends and accurately predict future tourist demand. They have been chosen due to their high accuracy and flexibility in capturing both linear and complex nonlinear patterns in tourism data. Regression Analysis is effective in identifying key factors influencing tourism trends, while LSTM models excel in handling sequential data and capturing long-term dependencies, making them ideal for precise forecasting.
Below, the mathematical and logical foundations of these models are discussed.

3.3.1 Regression Analysis

Montgomery, (2012) explained regression as a statistical technique used to model relationships between variables [27]. The Regression model will be utilized to:

- Analyze tourism trends to study the influencing factors. by studying the relationship between these factors and the tourism number.
- Develop a model to forecast future tourist numbers based on these independent factors.

Influencing factors include tourist types, reasons for visiting, tourist spending, season of weather, religious time, and pandemic time.

3.3.1.1 Mathematical Analysis

Linear regression

The basic form of regression, represented by the equation:

$$y = \beta_0 + \beta_1 x + \epsilon \text{ (1)}$$

where:

- $\boldsymbol{y}$ is the dependent variable.
- $\boldsymbol{x}$ is the independent variable.
- $\boldsymbol{\beta_0}$(intercept) and $\boldsymbol{\beta_1}$ (slope) are parameters.
- $\boldsymbol{\epsilon}$ is the error term.

○ **Multiple Linear Regression**

Extends linear regression to multiple predictors.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + (4)$$

○ **Ordinary Least Squares (OLS)**

The Ordinary Least Squares (OLS) method estimates regression coefficients by minimizing the total squared error between predicted and actual values. Each coefficient quantifies the independent effect of its corresponding feature on the target variable.

- For simple Linear regression model.

$$\min_{\beta_0,\beta_1} \sum_{i=1}^{n} \left(y_i - (\beta_0 + \beta_1 x_i)\right)^2 \text{ (5)}$$

To estimate β_0 and β_1.

The optimal values are calculated using:

$$\beta_1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2} \text{ (2)}$$

$$\beta_0 = \bar{y} - \beta_1 \bar{x} \text{ (3)}$$

where $\bar{y}$, $\bar{x}$ are the means of x and y.

- For Multiple Linear Regression

$$\min \sum_{\{i=1\}}^{n} \left(y_i - \left(\beta^0 + \beta^1 x_{\{i1\}} + \beta^2 x_{\{i2\}} + \ldots + \beta_p x_{\{ip\}} \right) \right)^2$$

Each β_p shows how much the target changes for each 1-unit increase in feature $x_{\{ip\}}$, holding other features constant.

- A large positive β_p → Strong positive effect on the target
- A large negative β_p → Strong negative effect
- A β_p near zero → Weak or no effect

3.3.1.2 Data Training and Testing

Training and splitting the dataset into three sets training, validation, and testing. These subsets will be used to train and evaluate the model. As shown in **Table**

Table 5. Datasets Splitting For Regression Model.

DATASET	SIZE	PROCESS
TRAINING	90% of the dataset (875 Records)	Training the model to forecast the total tourist over the years, monthly, based on the visiting reason and the tourism type, and other Influencing factors to capture the trends.
VALIDATION	10% of the dataset (97 Records)	Validate the model to forecast the total tourists over the years, monthly, based for the reason of visiting and the type of tourist, and other Influencing factors.
TESTING	10% of the dataset (108 Records)	Test the model to forecast the total tourist over the years, monthly, based on the reason for visiting and the type of tourist, and other Influencing factors that the model did not see.

3.3.2 Long and short-term memory

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Hochreiter, (1997) explained Long Short-Term Memory (LSTM) as the type of recurrent neural network (RNN) designed to handle long-term dependencies in time-series data [28]. Unlike traditional RNNs, LSTMs can prevent the vanishing gradient problem, allowing them to learn from long sequences. to forecast future tourism demand.
The LSTM model will be utilized in this research to forecast the future growth of the demand for tourism in Saudi Arabia. By using the historical data of tourism number.

Training face will depend on the tourism number over the years monthly

3.3.2.1 Mathematical Explanation

LSTM has components that work in a sequence:

1. **Forget Gate f_t**
   This gate determines what portion of the past cell state should be forgotten. It is computed as:

   $$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

   where:

   - The sigmoid function σ ensures the output is a value between 0 and 1, which acts like a filter to decide what to keep (values close to 1) or forget (values close to 0).
   - W_f and b_f are the weight matrix and bias.
   - h_{t-1} is the hidden state from the previous time step.
   - x_t is the current input.

2. **Input Gate i_t**
   The input gate controls how much new information should be stored in the cell state.

   $$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)(8)$$

   The values in this gate also range between 0 and 1. If the value is 1, the new information is fully accepted; if it is 0, the new information is ignored.

3. **Candidate cell state $\widetilde{C_t}$**
   This equation generates a new candidate memory state, which represents potential knowledge that might be added to the memory.

   $$\widetilde{C_t} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (9)$$

   The tanh activation function ensures values remain in the range of $[-1,1]$ 1][,1][-1,1], preventing excessive influence from extreme values.

4. **Cell State Update**
   The new cell state is a combination of the old state and the new candidate:

   $$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \ (10)$$

   Were

   - $\odot$ represents element-wise multiplication.
   - Two operations happen here:
     - **Forget gate action:** The old memory C_{t-1} is multiplied by f_t, controlling what is removed.
     - **New memory update:** The new candidate memory $\widetilde{C_t}$ is multiplied by i_t deciding how much to add.

5. **Output Gate o_t**
   This gate decides how much information from the cell state should be output:

   $$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)(11)$$

   The hidden state h_t is calculated by applying the output gate to the transformed memory state.

   The hidden state is then computed as:

   $$h_t = o_t \odot \tanh(C_t)(12)$$

These equations enable LSTM networks to remember important information while discarding irrelevant past data, making them useful for sequential predictions, such as time-series forecasting.

3.3.2.2 Data training and Splitting

Training and splitting the dataset into three sets training, validation, and testing. These subsets will be used to train and evaluate the model. As is shown below in **Table 7**:

Table 6. Datasets Splitting For LSTM Model.

DATASET	SIZE	DURATION	PROCESS
TRAINING	80% of the dataset (86 Months)	From 2015 to 2022-02	Training the model by using total tourists over the years, monthly, to capture the trends.
VALIDATION	20% of the dataset (22 Months)	From 2022-03 to the end of 2023	Validate the model by using total tourist over the years, monthly, to validate the trained model.
TESTING	Data never seen (36 Months)	From the start of 2024 to the end of 2026	Forecast the total tourist from the start of 2024 to the end of 2026.

3.4 Evaluation Metrics

To evaluate model performance, this study employs Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2). These metrics assess the accuracy, error magnitude, and explanatory power of both regression and LSTM models.

3.4.1 Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) explained by *James et al, (2013)* to measure the average absolute difference between the actual values and the predicted values [28]. It represents on average; the predictions differ from the true values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

Were

- y_i Actual value
- $\hat{y}_{i_i}$ Predicted value
- n Total number of observations

MAE is less sensitive to outliers compared to MSE. And does not penalize large errors as heavily as MSE does.

The regression model and the LSTM model use MAE to evaluate performance, as it provides an interpretable measure of average prediction error and an intuitive assessment of forecasting accuracy. MAE is less sensitive to outliers, making it appropriate for many real-world regression applications and time series forecasting tasks *James et al, (2013) and Brownlee, (2017)* [28; 29].

3.4.2 Mean Square Error (MSE)

The Mean Squared Error (MSE) explained by *James et al, (2013)* [28]. It calculates the average of the squared differences between actual and predicted values. It penalizes larger errors more than smaller errors due to squaring.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Lower MSE indicates better performance. And squaring the errors gives more weight to larger errors, making the metric sensitive to outliers.

MSE used to evaluate the performance of both the LSTM model and the regression model, as it is a widely accepted and effective metric for measuring predictive accuracy. In time series forecasting with LSTM, MSE is preferred because it penalizes larger errors and supports gradient-based optimization. Similarly, in regression analysis, MSE quantifies the average squared difference between actual and predicted values, giving more weight to larger errors and making it a standard choice for evaluating model performance in both academic and practical contexts [28;29].

R-squared R^2

The R^2 (coefficient of determination) measures how well the model explains the variability of the target variable. It ranges from 0 to 1, where 1 indicates a perfect fit and 0 means the model explains none of the variance.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Were

$\bar{y}$ Mean of actual values

It Shows the proportion of variance explained by the model. but does not directly indicate prediction error.

R^2 is a valuable evaluation metric for both regression and LSTM models, as it indicates the proportion of variance explained by the model, providing a clear measure of model fit and effectiveness across different predictive tasks [28].

Materials and Tools

This research relies on Python program through Jupyter Notebook which is a development environment for writing, testing, and documenting code interactively. To conduct all the work and a combination of tools, and libraries to preprocess data, perform analysis, develop models, and visualize results. Below is an overview of the tools and libraries used:

- **Pandas:** Used for data manipulation, cleaning, and restructuring operations such as merging, grouping, and pivoting datasets *McKinney and W, (2010).*
- **NumPy:** Supports numerical computations and efficient array processing *Harris et al, (2020)* [26].
- **Matplotlib and Seaborn:** Used for generating static and interactive visualizations, including correlation heatmaps, bar plots, and residual distribution charts *Waskom et al, (2021)* [30].
- **Scikit-learn:** Provides machine learning tools, including regression models (Linear, Polynomial), performance metrics, and preprocessing techniques *Pedregosa et al, (2011)* [31].
- **TensorFlow and Keras:** Utilized for building and training Long Short-Term Memory (LSTM) neural networks for tourism forecasting Chollet et al, (2015) [32] and Abadi et al, (2016) [33].

4 RESEARCH AND DISSCUSSION

4.1 Introduction

This chapter presents the results obtained from applying Regression Analysis and Long Short-Term Memory (LSTM) models to forecast Saudi Arabia's inbound tourism demand, alongside an analysis of the main influencing factors: tourist types, spending behavior, reasons for visiting, and seasonality. It is structured as follows: Section 3.2 Present the data exploration analysis for the research. Section 3.3 Discussion the regression analysis result. Section 3.4 Discussion the Long Short-Term Memory result. Finally, Section 3.4 Conclusions and findings.

4.2 Data Exploration

Exploratory Data Analysis (EDA) is a critical step in understanding the underlying patterns, relationships, and structure of a dataset prior to the implementation of predictive modeling [34]. In this study, EDA was conducted to assess the distribution of variables, detect outliers, and examine correlations among key attributes related to tourism demand in Saudi Arabia. To evaluate the relationships between the variables, a correlation matrix was generated, as shown in **Figure 1**. This matrix provides a standardized view of the linear relationships between numerical features, with correlation coefficients ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation). The diagonal elements all have a value of 1, as each variable is perfectly correlated with *Schober et al, (2018)* [35].

Several variables exhibit moderate correlations. Notably, there is a positive correlation 0.45 between visiting reasons and total tourists, suggesting that the purpose behind tourist visits has a moderate influence on the overall number of tourists. These reasons are ranked in importance starting with entertainment, visiting, religious, business and finally other reasons not known.

On the other hand, tourist types and total tourist are negatively correlated 0.46, which may indicate when one type of tourist becomes too dominant, the overall number of tourists drops.

In this case, total tourism tends to drop when the majority of tourists are inbound, and vice versa if it is domestic. Interestingly pandemic months variable shows a weak negative correlation with total tourists 0.095, reflecting a slight drop-in tourism activity during pandemic periods. Seasonality and religious months show weak associations with the other variables, reflecting that while these time-based variables are important contextually, their linear relationship with numeric attributes is limited.

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Figure 1. Correlation matrix.

To examine the correlation between tourist type and the total number of visitors, a stacked bar chart **Figure 2** was used to visualize the relative contribution of each tourist type across different travel motivations. The chart shows that entertainment and visiting reasons attract the highest number of tourists, primarily driven by domestic travel, reflecting strong local engagement in leisure and family visits, as well as the influence of national programs under Vision 2030. In contrast, religious reasons display a more balanced distribution between domestic and inbound tourists, aligning with Saudi Arabia's role as a central hub for Islamic pilgrimage, particularly during Hajj and Umrah. This category remains one of the strongest contributors to inbound tourism. In summary, the chart highlights that domestic tourism is the most dominant contributor to the total number of tourists in Saudi Arabia.

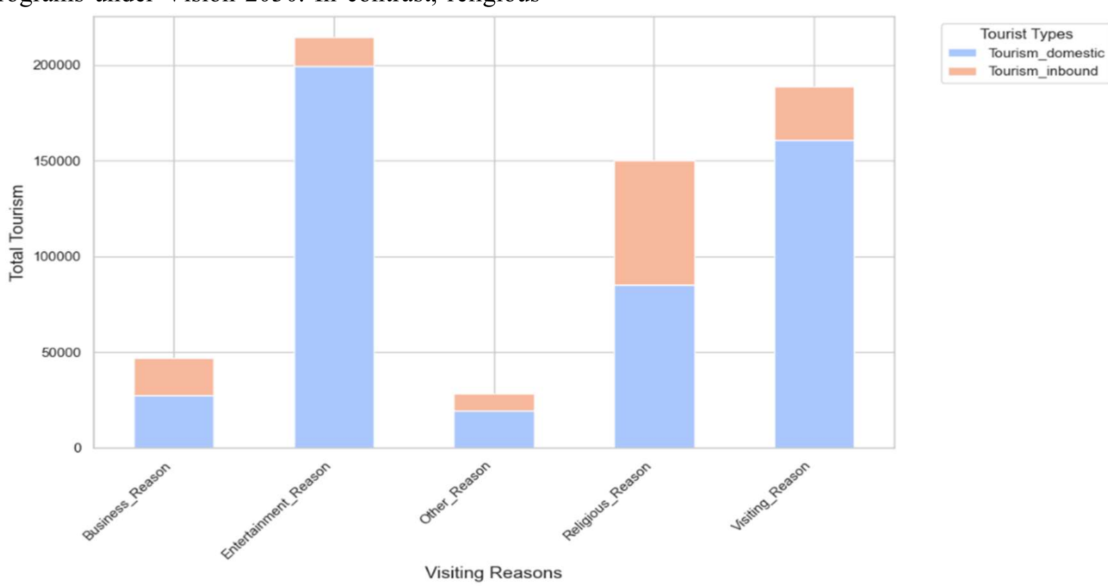

Figure 2. Total Tourist based on visiting reasons and tourist types

Figure 3 illustrates a clear inverse relationship between spending and the total number of tourists. As spending increases, the number of tourists declines sharply, suggesting that the majority of visitors belong to lower spending brackets. This trend indicates that tourism in Saudi Arabia is currently more concentrated in cost-sensitive segments, possibly reflecting the dominance of domestic tourism, which tends to have lower average expenditure per trip. The steep drop-off also highlights a relatively small proportion of high-spending tourists, pointing to potential opportunities for the development of premium tourism offerings to diversify the market.

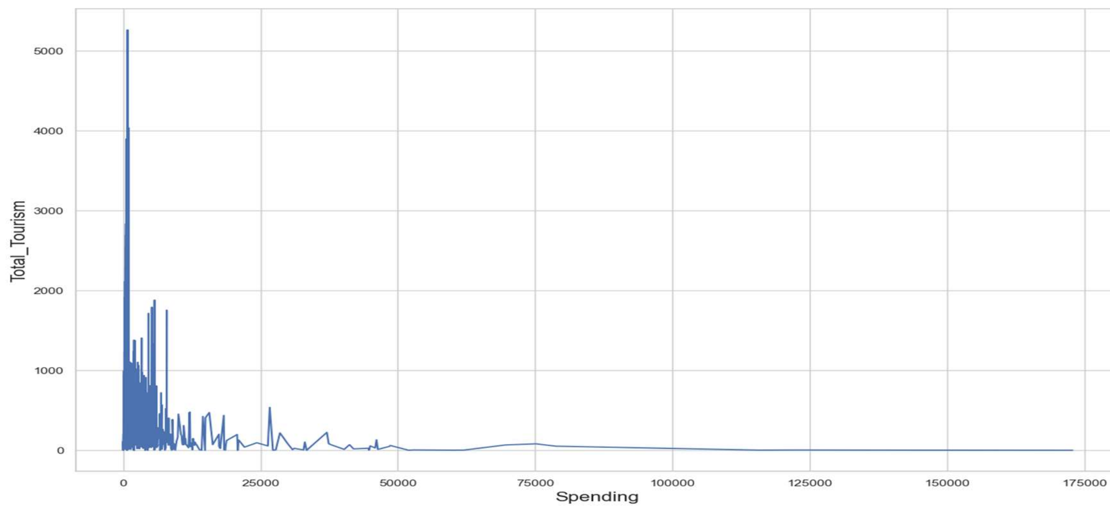

Figure 3 The impact of spending on the total tourist.

4.3 Regression Analysis Results

In line with the study's objectives to use a regression model to analyze the factors influencing tourism numbers and to forecast future tourist demand using regression models. Below are the results:

4.3.1 Analyzing Influential Factors

In Ordinary Least Squares (OLS) regression analysis, the coefficient indicates the direction and strength of the relationship between an independent variable and the dependent variable; a positive coefficient means that as the predictor increases, the outcome variable also increases, while a negative coefficient implies the opposite .The t-value assesses how many standard deviations the estimated coefficient is from zero, whereas a higher absolute t-value suggests stronger evidence that the variable has a meaningful effect. The p-value determines the statistical significance of the coefficient; a p-value below 0.05 typically indicates that the variable has a significant impact and the null hypothesis (that the coefficient is zero) can be rejected [36]

The result of OLS analysis shown in Table 7 to examine the impact of key variables, including tourist types, reasons for visiting, spending behavior, seasonal patterns, religious time, and pandemic time on total tourist arrivals.

Table 7. Ordinary Least Squares.

FEATURES	COEFFICIENT (B)	T-VALUE	P-VALUE
VISITING REASONS	244.80	20.34	0.00
TOURIST TYPES	(591.59)	(17.02)	0.00
SPENDING	(110.02)	(5.84)	0.00
SEASON	(6.75)	(0.45)	0.65
RELIGIOUS MONTH	69.99	1.52	0.13
PANDEMIC	(111.05)	(2.15)	0.03

The results above indicate that visiting reasons, tourist types, spending, and the pandemic are statistically significant predictors of total tourist. Visiting reasons have a positive effect, suggesting that specific travel motivations, such as entertainment or religious purposes, are associated

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with higher tourist volumes. Tourist types show the strongest negative effect, indicating that changes in the composition of tourists significantly reduce total tourists. Although spending is also statistically significant, its negative coefficient implies an inverse relationship with total tourists, which may be due to the concentration of most tourists in lower spending brackets. The pandemic variable also shows a significant negative effect, confirming that tourism activity declined during pandemic periods. In contrast, seasonal and religious months have higher P-values than 0.05, showing no statistically significant impact, suggesting that their influence on total tourist is limited or not captured well in this linear model.

4.3.2 Regression Model

In building regression models for forecasting, the training stage began with a baseline Linear Regression model, providing a simple benchmark for comparison. To capture potential nonlinear relationships between predictors and tourism demand, a Polynomial Regression model of degree 2 was then applied. Finally, a Polynomial Regression model of degree 3 was trained, offering greater flexibility in fitting the data

Table 8. Result of the Regression models.

MSE	MAE	R^2 SCORE
127,648.5	227.06	82.7%

As shown in **Table 9**, the Linear Regression model demonstrated the weakest performance, with a training R^2 score of 42.4%, a MSE of 193,696.89, a MAE of 358.36, and a testing R^2 score of 50.3%, indicating limited predictive accuracy. The Polynomial Regression model (degree 2) provided a notable improvement, achieving a training R^2 score of 76.0%, an MSE of 79,609.61, an MAE of 191.09, and a testing R^2 of 79.5%, reflecting better model fit and reduced error. The best performance was achieved by the Polynomial Regression model (degree 3), which further improved the results with a training R^2 score of 80.0%, a lower MSE of 75,801.67, a MAE of 181.57, and a testing R^2 score of 80.5%, confirming its superior ability to capture the complex, non-linear patterns affecting tourism demand [37].

To further support the conclusion that the Polynomial Regression model of degree 3 is the most effective among the tested models in **Figure 4**, a residuals distribution analysis was conducted. Residuals represent the differences between the actual and predicted values, and analyzing their distribution helps evaluate how well the model fits the data. A good model typically produces residuals that are randomly distributed and centered around zero, indicating minimal bias and stable variance *GeeksforGeeks. (2022, July 21)* [38] The resulting distribution confirms that the degree 3 model meets these assumptions, reinforcing its validity as the best-performing regression approach in this study.

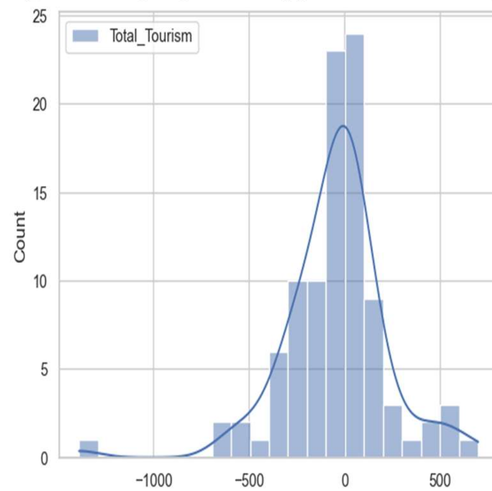

Figure 4. Residuals Distribution.

Finlay testing the model the results shown in **Table 10** represent the model's performance on unseen (test) data, which is critical for evaluating how well the model generalizes beyond the training set:

Table 9. Result of the Testing set for Regression Model.

MSE	MAE	R^2 SCORE
127,648.5	227.06	82.7%

These metrics confirm that the model performs very well on new, unseen data, making it a reliable forecasting tool for predicting tourism demand. The high R^2 and relatively low error values suggest that the model has not overfitted and generalizes effectively to real-world applications.

4.3.3 Long and short-term baseline results.

As a starting point, a simple baseline LSTM model was implemented using a single LSTM layer with 10 units [39]. This minimal configuration was used to establish a reference for model performance before tuning. The model was trained in the tourism time-series data and evaluated using standard regression metrics. The results were as follows in table **Table 11**:

Table 10. Baseline model Result for LSTM Model.

R^2 SCORE (TRAINING)	MSE (TESTING)	MAE (TESTING)	R^2 SCORE (TESTING)
-15.24	7,6654,682.06	8563.00	-22.02

Table 11 Advanced LSTM Model Results

MODEL TYPE	R^2 SCORE (TRAINING)	MSE (TESTING)	MAE (TESTING)	R^2 SCORE (TESTING)
LSTM 1 (NORMALIZE DATA)	0.103	0.073	0.22	-2.44
LSTM 2 (SEQUENCE WINDOWING =12)	0.05	0.06	0.21	-1.84
LSTM 3 (SEQUENCE WINDOWING =18)	0.07	0.051	0.18	-1.55
LSTM 4 (PARAMETER TUNING	-0.28	0.021	0.10	-0.06

These values indicate very poor predictive performance. In particular, the negative R^2 score suggests that the model performed significantly worse than a simple mean-based prediction. This highlights the limitations of under parameterized LSTM architectures to capture the underlying patterns in the tourism dataset.

4.3.4 Developing LSTM model

To evaluate the effectiveness of LSTM in forecasting tourism demand, four different model configurations were tested the results shown in

The first model, LSTM 1, involved only normalization of the input data, achieving an MSE of 0.103, MAE of 0.22, and an R^2 score of -2.44, indicating weak predictive capability and poor model fit. To improve performance, sequence windowing was applied in subsequent models, which involves restructuring the time series into overlapping sequences of fixed length to predict future values [28]. LSTM 3, which used a window size of 18, showed notable improvements over LSTM 1, reducing the MSE to 0.051, MAE to 0.18, and improving the R^2 score to -1.55. These results suggest that incorporating sequence windowing allowed the model to better learn temporal dependencies, although the R^2 remained negative, indicating that predictions still underperformed compared to a naive mean model. Nevertheless, the reduction in both MSE and MAE demonstrates that design choices like window size and temporal structuring significantly enhance LSTM model performance when applied to tourism time-series forecasting.

4.3.5 Generator and discriminator model.

To further enhance prediction accuracy in **Table 13**, we develop a model architecture based on a Generator and Discriminator framework

Table 12. Generator and Discriminator Model Result.

R^2 Score (training)	MSE (testing)	MAE (testing)	R^2 Score (testing)
54.5%	285,427.80	348.95	75.6%

The model achieved substantial improvements for forecasting performance compared to previous LSTM configurations. It reached a training R^2 score of 54.5%, indicating moderate explanatory power during learning, and generalization was further demonstrated by a MSE of 285,427.80, MAE of 348.95, and a testing R^2 score of 75.6%. These values reflect a significant reduction in prediction error and a strong ability to explain the variability in unseen data. This marks a major advancement over earlier LSTM models, which exhibited negative R^2 scores. The high R^2 confirms that integrating adversarial learning components specifically the Generator and Discriminator—effectively enhanced the model's capacity to capture complex temporal patterns and improved generalization in forecasting Saudi tourism demand.

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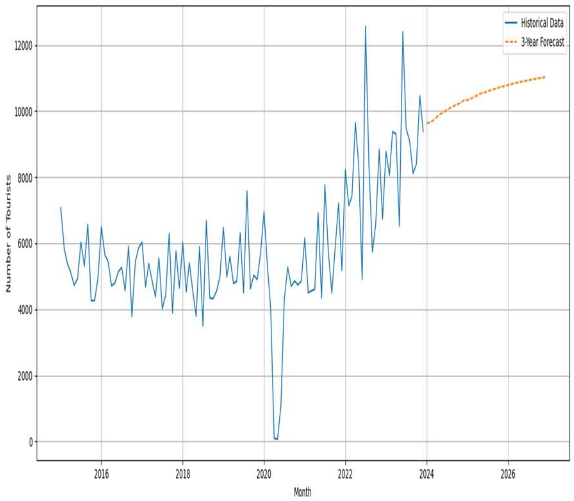

Figure 5. Tourism Forecast by LSTM for Next 3 Years.

Since the Generator–Discriminator LSTM model demonstrated the best performance among all tested models with a high R² score of 75.4% and significantly lower prediction errors it was selected for generating the 3-year tourism forecast. The graph in **Figure 5** illustrates both the historical monthly tourist data and the forecasted values extending from early 2024 through the end of 2026.

The model captures the general upward trend observed in recent years and projects continued growth in tourist numbers. The forecast line shows a gradual and steady increase, reflecting the model's ability to learn long-term patterns in the data without overreacting to short-term volatility.

4.4 Leveraging ARIMA model

In this section, we adopted the same ARIMA modeling structure as employed in a previous study by *Louati et al, (2024)* [10] which analyzed the same dataset to forecast tourism spending. While the earlier research focused on expenditure trends, my approach extends the methodology to forecast total tourist arrivals. Below in **Table 14** is the result of the model:

Table 13. ARIMA Model Result.

MSE (TESTING)	MAE (TESTING)	R² SCORE (TESTING)
12,512,797.09	3146.44	-2.65%

The ARIMA model produced suboptimal forecasting results, with a high Mean Squared Error (MSE) of 12,512,797.09 and a Mean Absolute Error (MAE) of 3,146.44, indicating substantial deviations between the predicted and actual tourist numbers. Furthermore, the model yielded a negative R² score of -2.65%, suggesting that it performed worse than simply predicting the average value across all observations. This negative R² highlights the model’s inability to explain the variance in the data, pointing to a poor fit and limited predictive capability in this context.

The ARIMA model's forecast, shown in **Figure 6**, extends the historical trend of total tourists over a 3-year period into the future using a dashed orange line.

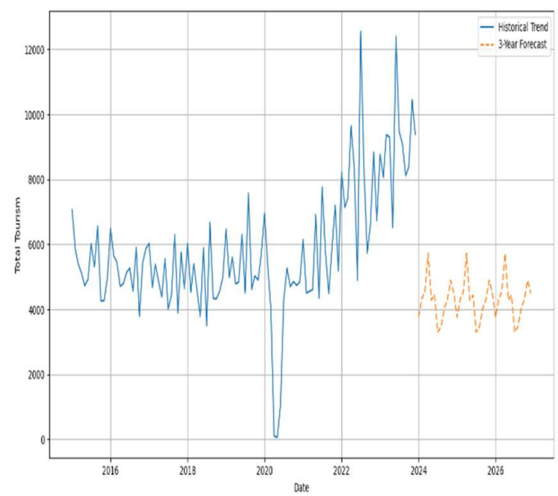

Figure 6. Tourism Forecast by ARIMA for Next 3 Years.

This project does not capture the sharp increases or volatility observed in recent historical data. This mismatch suggests that the ARIMA model's forecast is overly smoothed and lacks responsiveness to abrupt changes or recovery dynamics, likely contributing to its poor performance metrics. The model assumes consistent seasonality and linear trends, which are not aligned with real-world tourism dynamics.

4.5 FINDINGS

The results of this study demonstrate significant progress in identifying the key factors influencing tourism demand and in applying predictive analytics to the tourism sector in Saudi Arabia. Regression analysis revealed that four variables visiting reasons, tourist types, spending behavior, and pandemic

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periods had statistically significant effects on total tourist numbers. Specifically, visiting reasons had a positive impact, indicating that motivations such as entertainment and religious travel are associated with increased tourism.

Among the regression models tested, the Polynomial Regression model of degree 3 delivered the best performance, achieving a training R^2 of 80.0% and a testing R^2 of 80.5%, indicating that it explained over 80% of the variance in tourism numbers. This model also showed the most reliable residual distribution, confirming its ability to capture complex, non-linear relationships more effectively than simpler linear models.

In terms of deep learning approaches, the Generator–Discriminator LSTM architecture emerged as the top-performing model. It achieved a training R^2 of 54.5% and a testing R^2 of 75.6%, a substantial improvement over baseline and tuned LSTM models, which mostly yielded negative R^2 scores. This architecture successfully captured long-term dependencies and temporal patterns, demonstrating strong generalization to unseen data and making it highly effective for time-series prediction in tourism contexts.

Furthermore, when compared to the ARIMA model, which had previously been applied to the same dataset for forecasting tourism spending, the Generator–Discriminator LSTM model outperformed it significantly. The ARIMA model struggled to model non-linear and volatile patterns in tourism volume, producing a negative R^2 score of -2.65% and high prediction errors, underscoring its limitations for tourism demand forecasting.

In conclusion, this research confirms that machine learning models, particularly deep learning architectures like LSTM with adversarial components, offer a powerful alternative to traditional statistical models in forecasting tourism demand. They not only deliver better predictive accuracy but also provide richer insights into the dynamics shaping Saudi Arabia's evolving tourism sector.

5 CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

This study set out to analyze the key influencing factors behind tourism demand in Saudi Arabia and to develop accurate forecasting models aligned with the country's Vision 2030 tourism strategy. The research adopted a dual-method approach: regression analysis was used to examine the statistical significance of factors affecting tourism and to predict the total tourist based on these factors, while Long Short-Term Memory (LSTM) models were employed to predict future tourism trends based on time-series data.

The regression analysis identified visiting reasons, tourist types, spending, seasonal, religious time, and pandemic time as statistically significant predictors of total tourist. The Polynomial Regression model of degree 3 achieved the best results among the regression models, with a training R^2 score of 80.0% and testing R^2 score of 80.5%, indicating strong model fit and ability to explain over 80% of the variance in tourism demand. The residuals analysis confirmed its suitability in capturing complex, nonlinear relationships in the data.

In the deep learning phase, various LSTM configurations were tested. The most notable advancement was achieved using the Generator–Discriminator LSTM model, which outperformed all other LSTM variants. This model achieved a testing R^2 score of 75.6%, significantly reducing both MAE and MSE, and demonstrating excellent generalization on unseen data. It was also more effective than the ARIMA model used in earlier studies, which failed to capture non-linear and seasonal dynamics, resulting in a negative R^2 score of -2.65%. These findings demonstrate the advantages of deep learning architecture over traditional time-series models in capturing complex temporal patterns and structural changes in tourism demand.

Despite these contributions, several limitations should be acknowledged. The study relies on a limited number of explanatory variables due to data availability constraints, and other important tourism demand drivers such as international economic conditions, airline connectivity, or online travel search trends were not included. In addition, although deep learning models provide strong predictive accuracy, they remain less interpretable compared with traditional statistical models.

Overall, the findings of this research confirm that machine learning models particularly deep learning architectures offer powerful tools for forecasting tourism demand in complex, evolving environments. The integration of adversarial LSTM frameworks allows for accurate, scalable, and context-aware forecasting, providing valuable insights for strategic tourism planning in Saudi Arabia.

5.2 Future Work

Compared with previous tourism demand studies, this research integrates both determinant analysis and modern nonlinear forecasting approaches within a unified framework. While earlier Saudi tourism studies primarily relied on traditional econometric models such as ARIMA or ARDL, this study incorporates nonlinear regression and deep learning models to better capture complex demand dynamics. Additionally, the analysis explicitly models Saudi-specific calendar effects, including Ramadan and Hajj periods, as well as pandemic-related regime shifts.

Despite these contributions, several limitations remain. The analysis relies on a limited set of observable explanatory variables, and some tourism drivers such as international income levels, airline capacity, or online search behavior are not included due to data constraints. Moreover, deep learning models, while powerful for forecasting, remain less interpretable than traditional econometric approaches.

While this study has produced strong results, there are still opportunities to extend and enhance its contributions. Although this research already incorporated contextual features such as seasonality, religious periods, and pandemic time frames, future work can focus on expanding the temporal and spatial scope of the dataset. This includes incorporating higher frequency data such as weekly or daily records, or geographic segmentation by city, which would allow for more granular analysis and localized forecasting.

In addition, future studies could explore hybrid deep learning architectures, such as integrating attention mechanisms, transformers, or Seasonal Autoregressive Integrated Moving Average (SARIMA) and LSTM combinations to capture both linear seasonal components and non-linear temporal patterns more effectively

Finally, expanding the dataset with external variables such as international flight availability, global economic indicators, or digital engagement metrics such as social media trends and search data could further enhance model accuracy and provide deeper behavioral insights.

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