Journal of Advanced Research and Multidisciplinary Studies
ISSN: 2997-3155
Volume 5, Issue 1, 2025 (pp. 74-89)
www.abjournals.org

MODELLING THE INFLUENCE OF INFLATION ON FOREIGN TRAVEL DYNAMICS: A COMPARATIVE ANALYSIS OF LINEAR AND MACHINE LEARNING MODELS

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Cite this article:

Echeta, C. A., Aronu, C. O. (2025), Modelling the Influence of Inflation on Foreign Travel Dynamics: A Comparative Analysis of Linear and Machine Learning Models. Journal of Advanced Research and Multidisciplinary Studies 5(1), 74-89. DOI: 10.52589/JARMS-QEBGPVMW

Manuscript History

Received: 4 Jan 2025

Accepted: 14 Feb 2025

Published: 24 Feb 2025

ABSTRACT: *This study investigates the impact of inflation on foreign travel dynamics in Nigeria, focusing on the Headline Inflation Rate (HIR), Core Inflation Rate (CIR), and Food Inflation Rate (FIR) as predictors of the number of passengers travelling abroad (PPF) and the percentage of aircraft travelling internationally (PAF). Secondary data was employed in this study. The Central Bank of Nigeria Statistical Bulletin 2021 and the Federal Airport Authority of Nigeria (FAAN) records from 2015–2020 were the sources of secondary data. Correlation analysis, the linear regression model, the random forest regression model, and the gradient boosting regression model are among the statistical tools used. Correlation analysis revealed significant relationships among variables, with a strong positive correlation between PPF and PAF (0.95384) and between CIR and FIR (0.75894). In contrast, HIR exhibited weak negative correlations with PPF (-0.3024) and PAF (-0.24953). Linear regression models indicated statistical significance (F-statistic = 4.102, p = 0.0106), with HIR and FIR negatively impacting PPF (p = 0.0048, p = 0.0146, respectively) and CIR positively influencing it (p = 0.0419). However, these models explained only 18% of the variability in outcomes (adjusted R² = 0.1362). Machine learning models, particularly Random Forest, demonstrated superior predictive performance, explaining 51.24% and 55.23% of the variance in PPF and PAF, respectively, with the lowest RMSE values. Gradient Boosting also outperformed linear regression. HIR was the most influential predictor for PPF, while FIR dominated for PAF. These findings highlight the nuanced effects of inflation on travel dynamics and underscore the advantages of machine learning in policy modelling. Future research should explore additional factors, such as exchange rates and consumer confidence, to enhance understanding.*

KEYWORDS: Inflation, Foreign Travel Dynamics, Machine Learning Models, Random Forest Regression, Gradient Boosting Regression.

Article DOI: 10.52589/JARMS-QEBGPVMW
DOI URL: https://doi.org/10.52589/JARMS-QEBGPVMW

INTRODUCTION

Inflation, a critical macroeconomic indicator, exerts a profound influence on economic behaviour and decision-making, impacting sectors ranging from consumer goods to international travel. In Nigeria, where inflation has remained persistently high, understanding its implications on foreign travel dynamics is vital for formulating effective economic and transportation policies. Despite the extensive body of research on migration and macroeconomic factors, the specific role of inflation and its components—Headline Inflation Rate (HIR), Core Inflation Rate (CIR), and Food Inflation Rate (FIR)—in shaping foreign travel dynamics remains underexplored.

Prior studies have examined diverse macroeconomic factors influencing migration and travel behaviour. Zahniser (1999) analyzed Mexican migration patterns using a logit model, highlighting the persistence of migration and its nuanced relationship with socio-demographic factors but found limited explanatory power for wage differentials. Beihai and Akhtar (2023) focused on rural-urban migration in Pakistan, identifying GDP growth, inflation, and income inequality as significant determinants. While these studies provide valuable insights, they predominantly address broader migration patterns rather than specific travel behaviours linked to inflation. Bashyal and Subedi (2021) explored the intricate connection between labour diplomacy and migration governance, particularly in Nepal, where nearly a quarter of the working-age population works abroad, and remittances contribute over 25% of the gross domestic product (GDP). The study highlighted the socio-economic impact of labour migration, including gender dynamics, through qualitative analysis of government and international reports. It concludes that sustainable economic growth in Nepal is unattainable without harmonizing labour diplomacy and migration governance. Rayevnyeva et al. (2023) explored the impact of migration on gross domestic product (GDP) amidst globalization and the war in Ukraine. The study categorized migration into labour, educational, and refugee types, analyzing its general influence on GDP alongside factors like interest rate (IR), active population (AP), export (E), and consumer price index (CPI). Using vector autoregressive (VAR) models and Granger causality tests, findings revealed that migration negatively affects AP but positively impacts GDP. Impulse and decomposition analyses highlight a 10–14% mutual influence between migration and GDP, enhancing forecasting and understanding structural migration trends. Other research works have explored the impact of inflation in different contexts. Laurinavičius et al. (2022) investigated the influence of macroeconomic variables, including inflation, on housing markets in Vilnius, demonstrating its role in driving nominal house prices. However, its implications for travel behaviours remain underexplored. Furthermore, studies such as Cimpoeru (2020) and Lapid et al. (2022) employed traditional econometric approaches to analyze migration and economic trends. Cimpoeru (2020) used panel data regression to evaluate macroeconomic factors influencing migration in European countries, while Lapid et al. (2022) utilized time-series models to examine factors affecting overseas Filipino workers' movement. While these methodologies provide robust statistical insights, they may fail to capture the complex, non-linear relationships inherent in foreign travel dynamics.

Machine learning (ML) techniques, including Random Forest and Gradient Boosting, offer an innovative alternative to traditional econometric models. These methods are particularly suited for analyzing complex datasets with intricate interactions between variables. Despite their potential, the application of ML models in studying the influence of inflation on foreign travel dynamics remains largely unexplored. This study addresses these gaps by focusing on Nigeria,

Article DOI: 10.52589/JARMS-QEBGPVMW
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a country where inflation significantly affects economic activities and consumer behaviour. By modelling the relationship between inflation components (HIR, CIR, FIR) and foreign travel dynamics measured through the number of passengers travelling abroad (PPF) and the percentage of aircraft travelling internationally (PAF), this research provides novel insights into how inflation influences international travel patterns. Additionally, the comparative analysis of linear regression and ML models contributes to methodological advancements, offering guidance for selecting optimal predictive tools in similar contexts.

By filling these gaps, this study not only enhances the understanding of inflation's role in foreign travel dynamics but also provides actionable insights for policymakers to anticipate and manage travel-related economic activities amidst inflationary pressures. The findings are expected to inform transportation and economic policies, ensuring better alignment with Nigeria's development goals. The aim of this study is to model the influence of inflation on foreign travel dynamics in Nigeria, specifically focusing on the impact of the Headline Inflation Rate (HIR), Core Inflation Rate (CIR), and Food Inflation Rate (FIR) on the number of passengers travelling abroad (PPF), and the percentage of aircraft travelling internationally (PAF). The study compares the effectiveness of linear regression models with machine learning techniques (Random Forest and Gradient Boosting) in estimating these relationships. The objectives of the study are to: analyze the correlation between inflation variables (HIR, CIR, FIR) and foreign travel dynamics (PPF and PAF); evaluate the effectiveness of linear regression models in estimating the impact of inflation on foreign travel dynamics; assess the predictive performance of machine learning models (Random Forest and Gradient Boosting) in estimating foreign travel dynamics; compare the relative influence of inflation variables on foreign travel dynamics using machine learning models; and determine the most effective model for predicting foreign travel dynamics about inflation.

METHODS

METHOD OF DATA COLLECTION

In this research, secondary data has been used. Secondary data was collected from the records of the Federal Airport Authority of Nigeria (FAAN) from 2015-2020 and the Central Bank of Nigeria Statistical Bulletin 2021. The dataset includes the following variables:

Dependent Variables:

i. PPF (Passengers That Traveled to Foreign Countries): A measure of the number of passengers travelling abroad.

ii. PAF (Percentage of Aircrafts That Traveled to Foreign Countries): A measure of the percentage of aircraft involved in international flights.

Independent Variables (Inflation Rates):

i. HIR (Headline Inflation Rate): The general inflation rate including all goods and services.

ii. CIR (Core Inflation Rate): The inflation rate excluding volatile items like food and energy.

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iii. FIR (Food Inflation Rate): The inflation rate specifically for food items.

Method of Data Analysis Exploratory Data Analysis (EDA)

Prior to modeling, an exploratory data analysis (EDA) is conducted to understand the relationships between variables. This includes:

i. Descriptive Statistics: Summary statistics (mean, median, standard deviation, etc.) are calculated for each variable.

ii. Correlation Analysis: A correlation matrix is constructed to examine the strength and direction of the relationships between inflation variables (HIR, CIR, FIR) and the foreign travel indicators (PPF, PAF). This helps to identify potential linear associations and multicollinearity.

Model Development

i. Linear Regression Models

Linear regression is first applied to estimate the impact of inflation on foreign travel dynamics. The following models are developed:

Model 1: Estimating PPF

$$PPF = \beta_0 + \beta_1 HIR + \beta_2 CIR + \beta_3 FIR + \epsilon \tag{1}$$

Model 2: Estimating PAF

$$PAF = \beta_0 + \beta_1 HIR + \beta_2 CIR + \beta_3 FIR + \epsilon \tag{2}$$

where:

β_0 is the intercept,

β_1,β_2, and β_3 are the coefficients of the independent variables (HIR, CIR, FIR),

ϵ is the error term.

The models are estimated using Ordinary Least Squares (OLS), and the significance of the predictors is assessed using *t*-tests and *p*-values (Cohen et al., 2013). The goodness of fit is evaluated using R-squared and adjusted R-squared values.

Machine Learning Models

Random Forest Regression

A Random Forest regression model is employed to predict PPF and PAF. The Random Forest algorithm is an ensemble method that builds multiple decision trees and averages their predictions (Lavanya et al., 2023). The following parameters are used:

Number of Trees: Five hundred (500) trees are used to build the forest.

Variables at Each Split: One variable is tried at each split.

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Hyperparameter Tuning: To avoid overfitting, the model's hyperparameters, such as the number of trees and the number of variables at each split, are optimized using cross-validation.

The model's performance is evaluated by calculating the Mean Squared Error (MSE) and explaining the percentage of variance.

Gradient Boosting Regressions

Gradient Boosting is another machine learning technique employed to model PPF and PAF. Unlike Random Forest, Gradient Boosting builds trees sequentially, where each tree corrects the errors of the previous one (Khan et al., 2022). The model is trained with the following considerations:

Number of Trees: 500 trees.

Learning Rate: A learning rate of 0.1 is used.

Maximum Depth of Trees: The depth of each tree is limited to prevent overfitting.

The performance of the Gradient Boosting model is assessed by calculating the Root Mean Squared Error (RMSE) and the relative influence of each predictor variable on the response variable.

Model Evaluation

i. Performance Metrics

The models are evaluated using several performance metrics:

R-squared: Measures the proportion of variance explained by the model. A higher R-squared indicates a better model fit, which is commonly used to assess the explanatory power of regression models (Frost, 2020).

Adjusted R-squared: Adjusted for the number of predictors, it provides a more accurate measure of model fit when comparing models with different numbers of predictors. This adjustment accounts for the inclusion of non-significant variables, ensuring a more reliable metric for model evaluation (Miles et al., 2014).

Root Mean Squared Error (RMSE): Measures the average error between the predicted and actual values. Lower RMSE values indicate better model performance, as they reflect the closeness of predictions to observed values (Chai & Draxler, 2014).

Mean Squared Error (MSE): Used to assess the predictive accuracy of the Random Forest and Gradient Boosting models. MSE is a widely recognized metric for quantifying the average squared difference between predicted and actual values (James et al., 2013).

Variance Explained: The percentage of variance in the dependent variable explained by the model is used to compare the performance of machine learning models. This metric is particularly relevant in assessing the relative contribution of predictors in complex models like Random Forest and Gradient Boosting (Kuhn & Johnson, 2013).

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ii.Comparative Analysis

A comparative analysis is conducted to evaluate the relative performance of the linear regression, Random Forest, and Gradient Boosting models. This involves comparing the RMSE, MSE, R-squared, and variance explained for each model, with a focus on the predictive accuracy and robustness of the machine learning models.

iii. Variable Importance

The relative importance of inflation variables (HIR, CIR, FIR) in predicting PPF and PAF is assessed using the feature importance metrics provided by the Random Forest and Gradient Boosting models. These metrics indicate how much each variable contributes to the model's predictions, offering insights into the underlying relationships between predictors and outcomes (Lundberg & Lee, 2017).

iv. Ethical Considerations

The data used in this study is publicly available and does not involve any personal or sensitive information. All analyses are conducted by ethical research standards, ensuring the integrity and transparency of the findings.

RESULTS

Table 1: Descriptive Statistics of Percentage of Passengers That Travelled to Foreign Countries (PPF), Percentage of Aircrafts That Travelled to Foreign Countries (PAF), Headline Inflation Rate (HIR), Core Inflation Rate (CIR) and Food Inflation Rate (FIR) from 2015-2020

Test Measure	LOG(HIR)	LOG(FIR)	LOG(CIR)	LOG(PAF)	LOG(PPF)
Mean	0.0126	2.6280	2.3529	0.2716	0.1443
Median	-0.0097	2.6422	2.3115	0.4011	0.4047
Maximum	1.0121	2.9765	2.8197	0.5521	0.6981
Minimum	-0.8698	2.2486	1.9244	-1.5193	-3.6584
Std. Dev.	0.3480	0.2275	0.2503	0.4024	0.8753
Skewness	0.5289	-0.3136	0.2079	-2.8033	-3.1661
Kurtosis	3.3333	2.0746	2.2786	10.5083	12.585
Jarque-Bera	3.6910	3.7492	2.0797	4.9496	7.6826
Probability	0.1579	0.1534	0.3535	0.0841	0.0619
Observations	72	72	72	72	72

Descriptive statistics for five variables from 2015 to 2020 are displayed in Table 1. Headline Inflation Rate (HIR), Core Inflation Rate (CIR), Food Inflation Rate (FIR), proportion of passengers travelling overseas (PPF), and percentage of aircrafts travelling overseas (PAF) are the variables being examined. With LOG(HIR) averaging 0.0126, the mean is the average value. Standard deviation is used to quantify variability, and LOG(PPF) exhibits high variability (0.8753). Asymmetry is shown by skewness, with LOG(HIR) being positively

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skewed. Kurtosis and the Jarque-Bera test evaluate the normalcy and shape of the distribution, directing additional research.

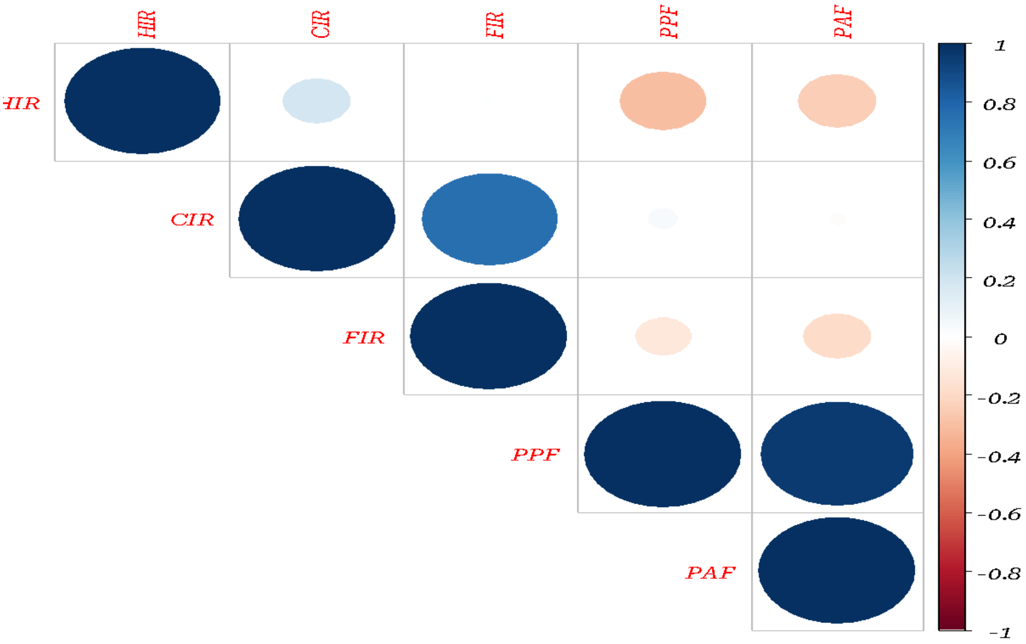

Figure 1: Correlation Heat Plot of HIR, CIR, FIR, PPF and PAF

The correlation matrix presented in Figure 1 reveals varying degrees of relationships among the variables. The strongest positive correlation is observed between Passengers that Travel to Foreign Countries (PPF) and Percentage of Aircrafts that travelled to Foreign Countries (PAF) (0.95384), indicating a very close linear relationship. Similarly, the Core Inflation Rate (CIR) and Food Inflation Rate (FIR) show a strong positive correlation (0.75894), suggesting these variables are closely linked. In contrast, Headline Inflation Rate (HIR) has weak negative correlations with both PPF (-0.3024) and PAF (-0.24953), implying a slight inverse relationship. Other correlations, such as between HIR and FIR (0.00573) or CIR and PAF (-0.01187), are negligible, indicating minimal or no linear association. These findings highlight key interactions and independence among the variables, with notable implications for modelling and analysis.

Article DOI: 10.52589/JARMS-QEBGPVMW
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Table 2: The Result of Linear Regression Model for Estimating PPF

Source of Variation	Estimate	Std.Error	t-value	Pr(>|t|)	
(Intercept)	2.0225	0.2958	6.8390	0.0000	***
HIR	-0.4902	0.1470	-3.3340	0.0015	**
CIR	0.0712	0.0301	2.3680	0.0214	*
FIR	-0.0618	0.0268	-2.3070	0.0248	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4173 on 56 degrees of freedom

Multiple R-squared: 0.1982, Adjusted R-squared: 0.1552
F-statistic: 4.6130 on 3 and 56 DF, p-value: 0.0059
Residuals:

Min	1Q	Median	3Q	Max
-1.2722	-0.1570	0.0651	0.2564	0.6028

The linear regression model for estimating PPF presented in Table 2 indicates that the model is statistically significant overall, with an F-statistic of 4.102 (*p*-value = 0.0106), suggesting that the predictors collectively explain a significant percentage of the variability in PPF. The multiple R-squared value of 0.1802 indicates that approximately 18% of the variation in PPF is explained by the model, while the adjusted R-squared value of 0.1362 accounts for model complexity. Individually, the intercept (1.9314, $p < 0.001$) is highly significant, showing the baseline level of PPF when predictors are zero. Among the predictors, HIR has a significant negative effect on PPF (estimate = -0.3135, $p = 0.0048$), indicating that an increase in HIR is associated with a decrease in PPF. CIR has a positive and significant effect (estimate = 0.0456, $p = 0.0419$), while FIR negatively impacts PPF (estimate = -0.0490, $p = 0.0146$). The residual standard error of 0.3032 suggests a moderate level of unexplained variability. These results highlight the differential impacts of the predictors on PPF, with HIR and FIR reducing, PPF and CIR contributing positively.

Table 3: The Result of Linear Regression Model for Estimating PAF

Source of Variation	Estimate	Std. Error	t-value	Pr(>|t|)	
(Intercept)	1.9314	0.2149	8.9870	0.0000	***
HIR	-0.3135	0.1068	-2.9350	0.0048	**
CIR	0.0456	0.0219	2.0830	0.0419	*
FIR	-0.0490	0.0195	-2.5190	0.0146	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3032 on 56 degrees of freedom

Multiple R-squared: 0.1802, Adjusted R-squared: 0.1362

F-statistic: 4.102 on 3 and 56 DF, p-value: 0.01059

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Journal of Advanced Research and Multidisciplinary Studies
ISSN: 2997-3155
Volume 5, Issue 1, 2025 (pp. 74-89)
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Residuals:

Min	1Q	Median	3Q	Max
-1.1135	-0.1049	0.0730	0.1798	0.4620

The linear regression model for estimating PAF presented in Table 3 reveals that the predictors significantly influence PAF, as indicated by an F-statistic of 4.102 (p = 0.0105). The model explains 18.02% of the variance in PPF (R-squared = 0.1802), with an adjusted R-squared of 0.1362, accounting for the number of predictors. The residual standard error of 0.3032 suggests moderate variability in the residuals. Key predictors include HIR, which has a significant negative impact on PPF (estimate = -0.3135, p = 0.0048), indicating that an increase in HIR reduces PAF. CIR positively affects PAF (estimate = 0.0456, p = 0.0419), suggesting its enhancement improves PAF. Similarly, FIR has a significant negative effect (estimate = -0.0490, p = 0.0146), indicating that higher FIR reduces PPF. These findings underscore the varying impacts of the predictors on PAF, with significant implications for policy interventions targeting these factors.

Table 4: The Result of the Random Forest Regression Model for Estimating PPF and PAF

Response Variable	Type of random forest	Number of trees	No. of variables tried at each split	Mean of squared residuals	% of Variance explained
PPF	regression	500	1	0.0988	51.2400
PAF	regression	500	1	0.0469	55.2300

The result of the Random Forest Regression model presented in Table 4 effectively estimates PPF and PAF, as evidenced by its performance metrics. For both response variables, the model used 500 trees with one variable tried at each split. The mean of squared residuals for PPF was 0.0988, with 51.24% of the variance explained, indicating moderate predictive accuracy. For PAF, the model performed slightly better, with a lower mean of squared residuals (0.0469) and a higher percentage of variance explained (55.23%). These results suggest that the Random Forest model is effective in capturing the variability of both PPF and PAF, with a slightly stronger performance for PAF.

Table 5: The Result of % of the Relative Influence of the Gradient Boosting Model for Estimating PPF and PAF

Response Variable	HIR	FIR	CIR
PPF	36.0047	35.2430	28.7523
PAF	32.9025	35.5067	31.5908

The Gradient Boosting model presented in Table 5 reveals the relative influence of predictors HIR, FIR, and CIR in estimating PPF and PAF. For PPF, the most influential predictor is HIR (36.00%), closely followed by FIR (35.24%), with CIR (28.75%) contributing the least. In the

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case of PAF, FIR (35.51%) has the highest relative influence, while HIR (32.90%) and CIR (31.59%) contribute slightly less. These results indicate that while all three predictors play significant roles, their relative importance varies slightly between the two response variables, with HIR dominating for PPF and FIR for PAF.

Table 6: The Summary Result of RMSE for the Estimation of PPF and PAF

Response Variable	Linear Regression	Random Forest	Gradient Boosting
PPF	0.5338	0.2911	0.2936
PAF	0.3986	0.2055	0.2599

The comparison of RMSE (Root Mean Square Error) values across models for estimating PPF and PAF presented in Table 6 highlights the superior performance of machine learning methods over linear regression. For PPF, Random Forest achieved the lowest RMSE (0.2911), closely followed by Gradient Boosting (0.2936), both significantly outperforming Linear Regression (0.5338). Similarly, for PAF, Random Forest again demonstrated the best performance with an RMSE of 0.2055, compared to Gradient Boosting (0.2599) and Linear Regression (0.3986). These results suggest that Random Forest provides the most accurate predictions for both response variables, making it a preferred choice for modelling PPF and PAF.

CONCLUSION

This study investigated the influence of inflation on foreign travel dynamics in Nigeria, with a focus on the Headline Inflation Rate (HIR), Core Inflation Rate (CIR), and Food Inflation Rate (FIR). The study also compared the predictive capabilities of linear regression models with machine learning techniques (Random Forest and Gradient Boosting) in estimating the number of passengers travelling abroad (PPF) and the percentage of aircraft travelling internationally (PAF). The findings provide valuable insights into the relationship between inflation components and foreign travel dynamics, as well as the comparative efficacy of traditional and advanced modelling techniques. The correlation analysis revealed significant interactions among the variables, with a strong positive relationship between PPF and PAF, and notable correlations between CIR and FIR. In contrast, HIR exhibited weak negative correlations with both PPF and PAF, suggesting an inverse relationship. These findings underscore the nuanced roles of inflation components in shaping travel behaviours. Linear regression analysis demonstrated that while the models were statistically significant, they explained only a modest proportion of the variability in PPF and PAF, with adjusted R-squared values of approximately 13.62%. HIR and FIR were found to have significant negative effects on PPF and PAF, while CIR positively influenced these outcomes. These results highlight the differential impacts of inflation components on foreign travel dynamics.

Machine learning models outperformed linear regression in predictive accuracy. Random Forest achieved the highest predictive performance, explaining over 50% of the variance in both PPF and PAF and exhibiting the lowest RMSE values. Gradient Boosting also performed well, with slightly lower accuracy than Random Forest but still surpassing linear regression. The relative importance analysis indicated that HIR was the most influential predictor for PPF, while FIR dominated for PAF. These findings emphasize the advantages of using machine

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learning models in capturing the complex, non-linear relationships between inflation components and foreign travel dynamics. The study's results provide a robust basis for developing targeted policies to mitigate the negative impacts of inflation on international travel.

Policymakers should prioritize stabilizing the Headline Inflation Rate (HIR) and Food Inflation Rate (FIR), as these significantly impact foreign travel dynamics. This could involve implementing monetary policies to control headline inflation and targeted interventions to address food price volatility. Given the strong correlation between the number of passengers travelling abroad (PPF) and the percentage of aircraft travelling internationally (PAF), investments in travel infrastructure, such as expanding international flight capacity and enhancing airport facilities, are essential to mitigate inflation's adverse effects. The superior performance of machine learning models underscores the importance of integrating advanced analytical tools into forecasting and decision-making processes within transportation and economic agencies. Broader economic strategies, including supporting agricultural productivity to reduce food prices, can help stabilize inflation and positively influence travel behaviour. Tailored interventions for the aviation sector, such as airline subsidies or traveller incentives, could further sustain international travel amidst inflationary pressures. Continuous monitoring of inflation's impact on travel dynamics is crucial, with future research recommended to explore additional factors, such as exchange rates, consumer confidence, and global economic conditions, to build a more comprehensive understanding of the drivers of foreign travel.

Conflict of Interest Statement

The authors hereby declare that they have no conflict of interest regarding the publication of this research.

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DOI URL: https://doi.org/10.52589/JARMS-QEBGPVMW

Journal of Advanced Research and Multidisciplinary Studies
ISSN: 2997-3155
Volume 5, Issue 1, 2025 (pp. 74-89)
www.abjournals.org

APPENDIX

R code used for the study

```
# Creating the dataset

> data <- data.frame(

 Year = c(rep(2015, 12), rep(2016, 12), rep(2017, 12), rep(2018, 12), rep(2019, 12), rep(2020, 12)),

 Month = rep(c("JAN", "FEB", "MAR", "APR", "MAY", "JUN", "JUL", "AUG", "SEP", "OCT", "NOV", "DEC"), 6),

 HIR = c(0.809457, 0.684534, 0.90996, 0.764947, 1.101403, 0.92578, 0.693917, 0.591822, 0.605439, 0.419025, 0.660366, 0.99483,

        0.867244, 2.303266, 2.174443, 1.610503, 2.751639, 1.714219, 1.252798, 1.006342, 0.813065, 0.825994, 0.784995, 1.055182,

        1.013487, 1.494588, 1.719129, 1.600862, 1.881355, 1.580364, 1.213127, 0.970303, 0.784822, 0.761868, 0.781648, 0.593268,

        0.799092, 0.791847, 0.836157, 0.834545, 1.089271, 1.237207, 1.132165, 1.048072, 0.836276, 0.739309, 0.801016, 0.738901,

        0.737848, 0.730099, 0.786599, 0.944142, 1.111361, 1.074451, 1.011354, 0.985718, 1.043229, 1.068237, 1.023682, 0.854229,

        0.873449, 0.789593, 0.839411, 1.019802, 1.167868, 1.213352, 1.246473, 1.34268, 1.477957, 1.535874, 1.602516, 1.614561),

 CIR = c(6.864695, 6.851567, 6.905164, 6.921936, 6.974742, 7.006292, 7.15355, 7.383852, 7.605135, 7.811633, 8.016061, 8.222145,

        8.391154, 8.732226, 9.131504, 9.614177, 10.19587, 10.86401, 11.55333, 12.24657, 12.98027, 13.75655, 14.54235, 15.30738,

        16.04245, 16.43626, 16.68243, 16.77233, 16.56717, 16.21913, 15.79842, 15.372, 14.90283, 14.41486, 13.92983, 13.45829,

        13.00963, 12.6684, 12.32951, 12.02053, 11.82784, 11.65148, 11.47824, 11.28498, 11.09167, 10.90309, 10.70325, 10.51379,

        10.33865, 10.18521, 10.04438, 9.909317, 9.770044, 9.640309, 9.52389, 9.411194, 9.336773, 9.253429, 9.188554, 9.154878,

        9.112089, 9.085726, 9.111948, 9.173582, 9.266553, 9.374952, 9.483871, 9.637896, 9.774946, 9.964805, 10.13643, 10.30806),

 FIR = c(9.474707, 9.485923, 9.494852, 9.50085, 9.509647, 9.534809, 9.552385, 9.570527, 9.61448, 9.680425, 9.778219, 9.897979,
```


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10.01672, 10.18421, 10.47094, 10.78593, 11.22144, 11.67236, 12.16238, 12.6958, 13.23756, 13.81737, 14.38552, 14.94624,

15.53581, 16.12741, 16.59835, 17.10628, 17.47719, 17.86784, 18.24735, 18.56908, 18.87619, 19.14031, 19.39223, 19.54616,

19.6208, 19.52143, 19.29389, 18.88601, 18.35916, 17.74518, 17.10161, 16.50127, 15.92278, 15.35532, 14.8021, 14.34829,

13.93406, 13.62022, 13.41963, 13.33917, 13.37068, 13.41801, 13.46023, 13.45819, 13.47421, 13.54398, 13.64592, 13.7428,

13.85866, 13.98037, 14.10866, 14.22063, 14.32537, 14.46006, 14.63383, 14.8692, 15.13495, 15.41639, 15.746, 16.1693),

PPF = c(1.637902, 1.137953, 1.441022, 1.483345, 1.523364, 1.449904, 1.576401, 1.89832, 1.791923, 1.794602, 1.472968, 1.816162,

1.634793, 1.278213, 1.508807, 1.512147, 1.489015, 1.414657, 1.559293, 1.857633, 1.607997, 1.422236, 1.23805, 1.628978,

1.449385, 1.100077, 1.155657, 1.313363, 1.358531, 1.31476, 1.472252, 1.860078, 1.777192, 1.361871, 1.367209, 1.751244,

1.565201, 1.184553, 1.426798, 1.555752, 1.452537, 1.540915, 1.687595, 1.802117, 1.751525, 1.466433, 1.529788, 1.946075,

1.68305, 1.171862, 1.432941, 1.611865, 1.585266, 1.558807, 1.877468, 1.959954, 1.799395, 1.5313, 1.607886, 2.010124,

1.880275, 1.37256, 0.859792, 0.025773, 0.031797, 0.04585, 0.293838, 0.126134, 0.292466, 0.43501, 0.597244, 0.842748),

PAF = c(1.602199, 1.419257, 1.65232, 1.552495, 1.619323, 1.553331, 1.536206, 1.57505, 1.640625, 1.642295, 1.518664, 1.586327,

1.524929, 1.455177, 1.614311, 1.582986, 1.61097, 1.487338, 1.465619, 1.615147, 1.468125, 1.511146, 1.31818, 1.475643,

1.374566, 1.201231, 1.234645, 1.182854, 1.357441, 1.350759, 1.440976, 1.641042, 1.598022, 1.489009, 1.468125, 1.486503,

1.495692, 1.319015, 1.455595, 1.470631, 1.525764, 1.460189, 1.574214, 1.570038, 1.68991, 1.511981, 1.535788, 1.737107,

1.491515, 1.390855, 1.644384, 1.683227, 1.477732, 1.554584, 1.639789, 1.581733, 1.598857, 1.447241, 1.534953, 1.656496,

1.550825, 1.373731, 1.055881, 0.218861, 0.298637, 0.402638, 0.65909, 0.487008, 0.595186, 0.545483, 0.920554, 0.991976)

)

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```
# View the first few rows of the dataset
> head(data)
# Calculate correlation matrix
> cor_matrix <- cor(data[, c("HIR", "CIR", "FIR", "PPF", "PAF")], use = "complete.obs")
> print(cor_matrix)
# Visualize the correlation matrix
> corrplot::corrplot(cor_matrix, method = "circle", type = "upper", tl.cex = 0.8)
# Split data into training and testing sets
> set.seed(123)  # For reproducibility
> train_index <- createDataPartition(data$PPF, p = 0.8, list = FALSE)
> train_data <- data[train_index, ]
> test_data <- data[-train_index, ]
# Define predictors and target variables
> predictors <- c("HIR", "CIR", "FIR")
> target_ppf <- "PPF"
> target_paf <- "PAF"
# Model for PPF
> lm_ppf <- lm(PPF ~ HIR + CIR + FIR, data = train_data)
> summary(lm_ppf)
# Model for PAF
> lm_paf <- lm(PAF ~ HIR + CIR + FIR, data = train_data)
> summary(lm_paf)
# Predictions
> lm_ppf_pred <- predict(lm_ppf, newdata = test_data)
> lm_paf_pred <- predict(lm_paf, newdata = test_data)
# Evaluation
> cat("Linear Regression RMSE for PPF:", rmse(test_data$PPF, lm_ppf_pred), "\n")
> cat("Linear Regression RMSE for PAF:", rmse(test_data$PAF, lm_paf_pred), "\n")
```


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```
# Model for PPF
> rf_ppf <- randomForest(PPF ~ HIR + CIR + FIR, data = train_data)
> print(rf_ppf)
# Model for PAF
> rf_paf <- randomForest(PAF ~ HIR + CIR + FIR, data = train_data)
> print(rf_paf)
# Predictions
> rf_ppf_pred <- predict(rf_ppf, newdata = test_data)
> rf_paf_pred <- predict(rf_paf, newdata = test_data)
# Evaluation
> cat("Random Forest RMSE for PPF:", rmse(test_data$PPF, rf_ppf_pred), "\n")
> cat("Random Forest RMSE for PAF:", rmse(test_data$PAF, rf_paf_pred), "\n")
# Model for PPF
> gbm_ppf <- gbm(PPF ~ HIR + CIR + FIR, data = train_data, distribution = "gaussian", n.trees = 5000, interaction.depth = 4)
> summary(gbm_ppf)
# Model for PAF
> gbm_paf <- gbm(PAF ~ HIR + CIR + FIR, data = train_data, distribution = "gaussian", n.trees = 5000, interaction.depth = 4)
> summary(gbm_paf)
# Predictions
> gbm_ppf_pred <- predict(gbm_ppf, newdata = test_data, n.trees = 5000)
> gbm_paf_pred <- predict(gbm_paf, newdata = test_data, n.trees = 5000)
# Evaluation
> cat("Gradient Boosting RMSE for PPF:", rmse(test_data$PPF, gbm_ppf_pred), "\n")
> cat("Gradient Boosting RMSE for PAF:", rmse(test_data$PAF, gbm_paf_pred), "\n")
```


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