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Forecasting Foreign Direct Investment to Sub-Saharan Africa using Arima Model: A Comparative Analysis of Machine Learning Algorithms

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Abstract:- This study examines the factors that influence individual foreign direct investment decisions and predicts using various Artificial Intelligence (A.I.) Algorithms models. The study also gives us an in-depth insight into the dynamics of complex FDI decisions using those A.I. predictive models. We use structural equation modeling in the prescriptive strand. Return on Investment (ROI), Security/Personal Safety, and Investment Facilitation Services significantly affect individual FDI decisions. On predictive strand analysis, we used various Machine Learning models to evaluate the accuracy of predicting classes of individual FDI risk decisions and the ARIMA model for prediction. We find that Random Forest and Ada Boosting Trees have substantial classification accuracies despite the "No free lunch" theorem. The result also indicates that a better prediction could be made by applying multiple classes of FDI inflow decisions rather than binary classes.

***Keywords**:- Foreign Direct Investment, Artificial Intelligence, Investment Facilitation, Return-On-Investment, Investment Decisions, Predictive Modeling, Random Forest, Gradient Boosting*

I. INTRODUCTION

Foreign direct investment (FDI) is an investment in long-term affiliation with a host country. It reflects a lasting interest being controlled by a resident entity in one economy by a direct foreign stakeholder or a parent enterprise in an enterprise resident or an economy different from that of the investor (United Nations, 2007). It should, however, be noted that foreign direct investment is different from indirect (portfolio) investment. FDI involves establishing a substantial, long-term interest in the economy of a foreign country.

Service quality is critically vital in providing companies with a competitive edge, as it influences various factors such as customer satisfaction (Osarenkhoe & Byarugaba, 2016)

It is well recognized in the economic literature that FDI plays a vital role in the financial growth process in host countries, and since FDI is considered a vehicle to shift new ideas, capital, improved technology, and new skills from advanced countries to emerging countries. Specifically, Return on Investment (ROI) is broadly used for analyzing the performance of investments in a business or investments for an individual (Brauer, 2016).

Data analytics (DA) examines data sets to determine the information they contain, increasingly with the support of specialized systems and software.

ARIMA models could generate projections for varieties of time series data. It is worth noting that the ARIMA model has three parts. However, not all aspects are always required, but it depends on the type of time-series dataset available. The three parts are the autoregressive (A.R.), the integrated (I), and finally, the moving average (M.A.). The assumption for the A.R. part of a time series dataset is that the observed value varies on some linear combinations of prior observed values up to some upper limit lags plus an error term. The assumption for the M.A. part of time series data is that the practical estimate is a random error term plus some linear permutations of previous random error terms up to some maximum lags (Stanley Jere, 2017).

The forecasts by the gradient boosting model and, of course, the random forest model is more precise than the target forecasts. In comparison between the gradient boosting and random forest models, the gradient boosting model turns out to be more specific (Yoon, 2020)

Generally, forecasting outcomes play a fundamental role for policymakers, economic decision-makers, and other key stakeholders with the view of coming up with reasonable policies and suitable strategic plans but all those depend primarily on the accuracy of the forecasts.

The main objective of this study is to conduct empirical research on the most effective A.I. application and propose appropriate recommendations to promote and facilitate investment in African Sub-Region based on predictive inference.

This is in tune with the Sustainable Development Goals to promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all, especially in Sub-Saharan African regions (Nations, 2022). Given the foregoing, it is deemed critical that each African country has to do much self-diagnosis in the perspective of strategic thinking on how best to entice FDI and link it with the local economy so as to develop linkages that would contribute to maximizing returns at the local level (David Brady, 2010).

This paper contributes to the literature on FDI and economic growth and the importance of integrating investment

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promotion with investment facilitation to lure potential investors. We slightly deviate from previous studies by comparing the predictive patterns of two classes of investment against multiple classes in the contexts of FDI inflows decisions using ML models.

Our main focus as predictive analysts is to develop a descriptive and then predictive research report that will help critical stakeholders better understand the predictive propensity of the combined factors for investment policy to make informed decisions.

Preliminary findings indicate that certain individual decision factors of the FDI significantly impact individual FDI decisions. Also, they are expected to be essential factors in predicting the class of investment relative to other select factors. To gain a deeper insight into various Machine Learning models in the context of investor multi-layered investment decision factors for FDI, we ask these questions:

(1) To what extent do FDI decision factors contribute to determining the ideal choice of the best A. I model for prediction, and (2) How and to what extent does the class size of the target FDI decision variable determine its predictability?

The research questions are shaped by the purpose of the study and form the methods and the design of the analysis. The research questions have enabled us to identify and produce interesting hypotheses and ML models that infer and predict individual decisions for key stakeholders. Given its generalizability, R&D Units in the Investment Promotion Agencies (IPAs) can easily replicate the method and apply new data to forecast FDI inflows based on investment decisions based on select factors.

However, policymakers often find modern-day scholarship less than helpful when it employs such methods across the board for their benefit and without a clear sense of how such a study would contribute to investment policymaking (Paul C. Avey, 2014). This makes us suggest strategic collaboration with academia or consultants.

The proposed use of combined descriptive and prescriptive models will be used to predict FDI inflows for years to come in the face of current global economic challenges and lingering insecurity in the African Sub-Region. The forecasts from this study will help governments in Africa enhance FDI inflows that would revamp economic growth. The central aim is to identify key contributing factors of Foreign Direct Investment decisions in the African Sub-Region, find out their effectiveness, assess the efficacy of various predictive classification models, and forecast FDI inflow to African Sub-Region based on investment decisions. The findings of this study would go a long way in formulating economic and investment policies with a view to strategic decisions to attract beneficial FDI to African Sub-Region. Figure 1 depicts the hypothesized model.

Artificial intelligence (ML) models would be used to predict the future inflow of FDI based on investment decisions by foreign investors using the FDI data obtained from an online survey (Qualtrics software). This study will apply FDI inflows measured from 2006 to 2018. In this study, because of the limited sample size, no shrinkage methods algorithms have been used for variable selection to select models for predicting FDI decisions.

II. RELATED STUDIES

A. *An overview of the FDI*

Foreign Direct Investment, called FDI, is an investment in a business by an investor from another country for which the foreign investor controls the majority of company purchases. In addition, the International Monetary Fund's Balance of Payments Manual defines Foreign Direct Investment as an investment that is made to obtain a lasting interest in an enterprise operating in an economy other than that of the shareholder. The investor's purpose is to actively influence the enterprise's management (Moosa, 2002).

B. *Factors influencing the FDI decisions:*

- *Investment incentives perception.*

Investment incentives also include procedures designed to influence an FDI project's size, locality, or industry by affecting its relative cost. It also alters the risks attached to it through inducements that are not available to comparable domestic investors (OECD, 2019). Investment incentives are the reward for and an encouraging force behind the investment, the object of which is usually to maximize return (McGraw, 2016).

Investment incentives are designed to minimize a firm's tax liability. They include tax allowances such as a reduced corporate income tax rate, tax holidays; accelerated devaluation allowances on capital taxes; exemptions from import duties, and duty drawbacks on exports. However, businesses do not always succeed.

- *Ease-of-doing-business perception.*

The ease of doing business index, known as EDB, ranks the controlling (institutional) environment in countries around the world in terms of tasks for running a business (Simmons, 2019). EDB includes starting a business, getting credit, getting electricity, paying taxes, and trading across borders, among other things (Nau, 2018). Corcoran and Gillanders (2014) indicate that EDB is an inherent proxy for trade costs. A high level of Ease of Doing Business means the regulatory environment is more conducive to starting and operating a business. In an empirical study on the effects of EDB, Kelley found that the EDB ranking generally shapes positive investors' perceptions of opportunities (Doshi, Kelley, & Simmons, 2019). However, they find no evidence that perceived EDB affects the FDI that a country gets (Corcoran & Gillanders, 2014).

➢ *Foreign exchange rate manipulation*[1].

Exchange rates are the value of one exchange relative to another. In theory, it reveals the relative suitability of a currency pair, with the simple economic principle of expecting money to flow towards a stronger currency. It is simply the proportion of exchange for two currencies (Loftus, Leo, Daniliuc, & Boys, 2020). It is the amount of exchange that one needs to pay to buy one unit of a different currency (Zakamulin, 2017).

A previous study indicated that the regression effects of exchange rate depreciation (EXC) have a considerable positive impact on FDI inflows into Nigeria (Nurudeen, Wafure, & Auta, 2011). However, the coefficients of error correction of FDI flow and foreign exchange rate are substantially negative, while that of natural resource outflow and GDP are significantly positive. Foreign exchange appreciates with FDI inflow and resource outflow (Dinda, 2008).

➢ *Return on investment perception (ROI).*

ROI is the total anticipated discounted stream of net profits divided by the costs of the investment (PMI, 2017). Return on investment (ROI) is broadly used for evaluating the execution of investments in a company or investments for an individual (Brauer, 2016). A different study by Wensveen (2016) discovers that return on investment (ROI) is a vital measure of an industry's and individual firms' capabilities to attract capital for sustained growth and replacement of existing assets. In addition, an empirical study by Alavinasab (2013) used an econometric simulation to reveal significant positive effects of return on investment on FDI. He also contends that the viability of an investment is one of the significant contributing factors to FDI (Alavinasab, 2013).

➢ *Corruption perception.*

Certain countries remain unable to attract FDI despite high levels of corruption (Kolstad & Villanger, 2008). Ufere Perelli, Boland, and Carlsson (2012) indicate that local executives are active perpetrators of bribery, which is another form of corruption rather than casualties of the bribe-demanding government. Greppin, Carlsson, Wolfberg, and Ufere (2017) also found that when executives give way to extortion, they commonly do so because they feel they have no choice.
Additionally, it has been established that only by paying bribes would they be able to get resources out of institutions, get new business, avoid retaliation, enable their company to flourish, or prevent their company from being shut down (Greppin et al., 2017).

➢ *Security/personal safety perception.*

Security is the State of being or at least feeling safe, and, in particular, the safety of a country or an organization against illicit activities such as extremism or espionage, and other potential dangers (Badie, Berg-Schlosser, & Morlino, 2011). In a broad sense, security encompasses the protection of physical and digital assets, which may be physical, personal or building, or informational (Nemati, 2017). Safety factors are influenced by perceived reality and are a subtle combination of technical and emotional aspects (Geetika, Ghosh, & Chowdhury, 2015). Therefore, to a prospective investor, as in the medical field (Kostelnick, 2014), safety is a high priority in FDI decisions.

Brown and Hibbert (2017) analyzed the impact of violent crime on foreign direct investment (FDI) inflows in a sample of 62 countries from 1997 to 2012. Their findings indicate that violent crime acts as a deterrent to FDI because criminal activities have the potential to increase the cost of doing business. They also reduce the demand for goods and services (Brown & Hibbert, 2017).

➢ *Investment promotion perception.*

Narrowly defined, investment promotion consists of advertising, direct mailing, investment seminars, and investment missions (Kitchin & Thrift, 2009). An investment promotion agency (IPA) is often a government agency whose mission is to attract investment to a country, State, region, or city. Generally, IPA services have four core functions: image building of FDI hosting country, investment generation, project management, and aftercare services (wikipedia, 2018). While IPAs play an essential role in enticing investment to developed countries, some IPAs have additional advocacy functions.

Essential investment promotion services include attracting foreign direct investment (FDI) or enhancing domestic investment, which requires a wide range of efforts. (World Bank, 2010).

Morisset argues that the perception of investors of the efficacy of IPAs is highly reliant on the quality of the investment climate and the level of development of the country (Morisset & Andrews-Johnson, 2004). He concludes that when the investment climate is poor, excess resources have to be spent on convincing potential investors. However, a study by Harding and Javorcik (2011) suggests that to some investors, investment promotion does in developing countries but not in technologically advanced economies.

➢ *Investment facilitation perception.*

Karl (2018) and Sauvant (2015) define investment facilitation not as a matter of promotion-as-usual but as a means of finding and diffusion of new approaches and applications, a process that needs nurturing and support (Sauvant & Hamdani, 2015). Investment facilitation usually takes place through an investment promotion agency (IPA). Typically through a government agency whose mission is to attract investment to a country, State, region, or city (Korinek & Sourdin, 2011) (OECD, 2011).

C. Modeling FDI Prediction using Machine Learning (ML) models

Not enough literature is known about how machine learning could be used to predict specific individual Foreign Direct Investment (FDI) decisions in the Sub-Saharan African region.

[1] Exchange rate changes due to manipulation increase the risk and uncertainty for investors

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In reality, it is hard to predict future values of FDI because linear models sometimes can't capture the complex designs in the data. It is anticipated that estimation of FDI through the deep learning process would not only be able to capture such unpredictability more efficiently. Efficiently but also be able to forecast future inflows of FDI more accurately than traditional forecasting procedures (Roy, 2020).

By using the dataset from the period 1970-2009, Pradhan (2010) finds that Artificial Neural Network (ANN) is an effective tool for forecasting FDI. This supports the evidence that it is possible to extract information hidden in FDI and make future forecasts regarding FDI inflows (Pradhan, 2020).

A study by Stanley (2017) found that in comparison of the three methods used shows that the ARIMA (1, 1,5) is the best fit model to predict FDI because it has the minimum error. He concludes that decision-making on coming up with reasonable policies and suitable strategic plans depends on the accuracy of forecasts (Stanley Jere, 2017).

Another study that combined ARIMA and ANN models in linear and non-linear modeling indicates that the combined model could effectively improve forecasting accuracy achieved by either of the models used separately (G.PeterZhang, 2003).

An article by Javier Arroyo (2009) proposed adapting the k-NN method to forecasting HTS and yielded promising results. The extension of the proposed method allows the direct inclusion of lagged values of explanatory time series. It could be beneficial in some applications (Javier Arroyo, 2009).

A study by Akbar (2014) finds that N.N. approaches better explain FDI determinants' weights than traditional regression methodologies. However, their preliminary findings offer essential and novel implications for future research in this area (Akbar & Yusaf, 2014).

The accuracy of any forecast is measured by mean absolute percentage error and root squared mean error. Another empirical study indicates that the gradient boosting and random forest models' predictions are more accurate than the benchmark forecasts. Between the gradient boosting and random forest models, the gradient boosting model turns out to be more precise (Yoon, 2020).

A different study by Wu (2021) conducted three experiments by testing the predictive ability of the decision tree algorithm, testing the decision tree algorithm with performance improvements, and determining the best decision tree forecast rate comparison. And using the logistic regression model indicates that the random forest has the highest and best prediction rate in contrast with the logistic regression model (Wang, Jen-Hsiang, & Pei, 2021).

However, Nyawedzeni (2018) used the shrinkage selection methods of elastic net, least absolute shrinkage, and selection operator (Lasso) for the choice of best variables. He discovered that linear quantile regression averaging was the best model to predict foreign direct investment since it had 100% coverage of the predictions, and the averaging was also confirmed to be the best model under the forecast error distribution (Netshivhazwaulu, 2018). Len (2020) concludes that the prediction indexes selected after quantification based on the random forest could improve the prediction accuracy (Lei Wen, 2020).

III. METHODS

The explanatory models would be built with the use of SPSS-AMOS regression analytical applications. The focus would be on direct effect regression of the predictors on the target variable. The second part would be identifying the most effective models for predicting FDI decisions and their application to making a forecast.

- *Description of the design.*

This is a two-level exploratory sequential method research design where we begin by exploring the quantitative data and analyzing it, then build models to be validated (Creswell & Creswell, 2018). The next level of the study builds on the results of the initial findings to make predictive inferences (Creswell & Creswell, 2018: 224). The first part of the study strand is motivated by the desire to examine the significance of individual investors' FDI perception factors that shape investors' risk preferences. The second strand is inspired by the need to have a better understanding of whether the predictive models are good enough to predict decisions and the third strand is motivated by the desire to make predictions of FDI decisions over the next ten years.

- *Source data for Descriptive Analysis*

In this study, we used preexisting data obtained from various FDI-relevant stakeholders both in Nigeria and in the diaspora using Qualtrics that had some forms of investment in Nigeria from the year 2006 to 2018 (Yusuf, 2020).

The sampling and data collection, participants, procedure, constructs, and measures are explained in the previous studies (Yusuf, 2020).

A. Hypotheses for Structural Equation Model

- *Individual FDI Perception Factors*

The investment climate is routinely viewed to be the primary (and sometimes the only) FDI determinant. However, FDI allocation lies beyond investment climate alone since investors from different countries estimate investment climates differently (Panibratov, 2017). Ease of doing business is a major determining factor that attracts FDI into a country. That is especially true for those potential investors that rely heavily on the World Bank's ease of doing business country ratings. The study by Hossain, Hassan, Shafiq, and Basit (2018) found that ease of doing business indicators significantly and positively impact Inward FDI. The study posits that the ease of doing business enables inward FDI through better contract enforcement, getting credit, and registering property. I assert that:
Hypothesis 1. Ease of Doing Business Perception positively affects Foreign Direct Investment (FDI) inflow.

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The attitude towards inward foreign direct investment (FDI) has changed considerably over the last few years. Many host countries have liberalized their economic policies to attract foreign multinational corporations (MNCs) investment. Nigeria is no exception. These include fiscal incentives such as tax holidays and lower taxes for foreign investors; financial incentives such as grants and preferential loans to MNCs. And measures such as market preferences, infrastructure, and sometimes even monopoly rights (Blomström, Kokko, & Mucchielli, 2003). A study by Roberts (1993) on determinants of FDI incentive preferences of MNEs finds that government programs waiving import duties were deemed most important by their targeted investors (Rolfe, Ricks, Pointer, & McCarthy, 1993). I thus posit that:
Hypothesis 2. Investment (Business) Incentives Perception positively affects Foreign Direct Investment (FDI) inflow.

Return on investment (ROI) is an essential measure of an industry's and individual firms' ability to attract capital for continued growth and replacement of existing assets (Wensveen, 2016). No investor would like to venture into a business that has a low ROI. However, some investors from a particular region of the globe do not give it a priority; instead, they look at other factors like security and ease of doing business. High ROI can make it much easier for host nations to experience an influx of investors, and they are expected to sharpen their skills in handling business registration and other processes. An empirical study by Alavinasab (2013) used an econometric model to detect significant positive effects of return on investment on FDI. He argues that the profitability of an investment is one of the essential determinants of FDI (Alavinasab, 2013); thus, I posit that:
Hypothesis 3. Return on Investment Perception has a positive effect on Foreign Direct Investment (FDI) inflow.

A study on the effect of corruption on foreign direct investment inflows in Sub-Saharan Africa by Omodero (2019) finds that Nigeria's corruption ranking position has an insignificant positive impact on FDI. The implication is that Nigeria's poor institutional and legal framework qualities are helping corruption to thrive in all areas of Nigeria's economy (Akinlabi & Hamed, 2011). A similar study on corruption, foreign direct investment, and economic growth in Nigeria by Akinlabi and Hamed (2011) found that there is a long-run relationship between FDI inflow and a low level of corruption. It is suggested that for Nigeria to attract a large volume of FDI inflow, corruption at all levels of governance must be drastically reduced and checkmated. However, some countries continue to attract FDI despite high levels of corruption (Kolstad & Villanger, 2008). Cuervo-Cazurra (2006) argues that corruption results in a reduction in FDI and a change in the composition of the country of origin.

From a different perspective, a study by Ufere et al. (2012) found that local managers are active perpetrators of bribery rather than victims of the bribe-demanding government. Greppin et al. (2017) found that when executives decide to succumb to extortion, they generally do so because they feel they have no choice: only by paying bribes will they be able to get materials out of customs, get new business, avoid retaliation, enable their company to thrive, or prevent their company from being shut down. I posit:
Hypothesis 4. Corruption Perception has a negative effect on Foreign Direct Investment (FDI) inflows.

Over the past decade or more, Sub-Saharan Africa has witnessed unprecedented security challenges occasioned by the activities of militants in the south-south region, kidnappers in the southeast, violent armed robbery in all parts of the country, political assassination, ritual killings, and more recent activities of Boko Haram in some parts of the northern Nigeria region, especially northeast. When put together, these social menaces impinge on the security of lives and property of Nigerian citizens and foreigners living or even trying to invest in the country (Udeh & Ihezie, 2013). These menaces trigger a problematic sense of insecurity that challenges Nigeria's efforts toward national economic development and, consequently, its Vision 20:2020. It also reduces the attractiveness of foreign investment and its contributions to economic growth in Nigeria (Udeh & Ihezie, 2013).

This indicates a profound negative impact of insecurity on FDI inflows to the country. Thus, I posit that:
Hypothesis 5. Security/Personal Safety Perception has a negative effect on Foreign Direct Investment.

Despite the ambiguous evidence on the benefits of FDI, investment promotion has become an active area of policy, and a growing number of nations are offering services and incentives to attract investment from multinational firms. Andrew (2015) finds that the positive effect of investment promotion on FDI inflows is robust across various empirical specifications (Charlton & Davis, 2017). In support, a previous study by Harding and Javorcik (2011) finds that investment promotion leads to higher FDI flows to countries in which red tape and information asymmetries are likely to be severe. The study suggests that investment promotion works in developing countries but not in industrialized economies. Essential investment promotion services include attracting foreign direct investment (FDI) or enhancing domestic investment; (World Bank, 2010). The apex investment promotion agency, NIPC in Nigeria, contributes to minimizing capital flight by providing existing investors with aftercare services at no cost. By so doing, it helps reduce the problems of low Ease of Doing business for investors; Thus, I posit that:
Hypothesis 6. Investment Promotion Service Perception has a positive effect on Foreign Direct Investment.

Foreign Exchange refers to uncertainty and risk associated with the manipulation of the exchange rate. Foreign exchange rate uncertainty affects managers' and risk-neutral multinational firms' foreign direct investment decisions (MNCs). An empirical study by Sung and Lapan (2000) on Strategic foreign direct investment and exchange rate uncertainty finds that the firm can increase expected profits with sufficient exchange-rate volatility.

A previous study indicated that exchange rate depreciation (EXC) significantly impacts FDI inflows into Nigeria

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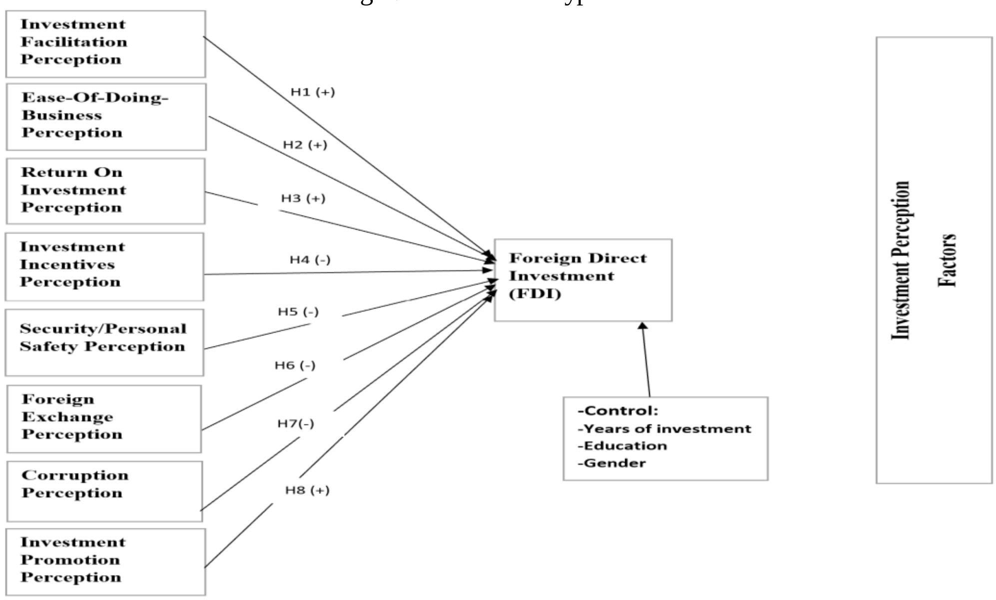
(Nurudeen et al., 2011). However, the coefficients of error correction of FDI flow and foreign exchange rate are significantly negative, whereas that of natural resource outflow and GDP are quite positive. FDI flow and resource outflow directly influence the foreign exchange rate.[2] Foreign exchange appreciation with FDI inflow and resource outflow (Dinda, 2008). Stevens (1998) found statistically significant evidence of the implied negative relationship between exchange rates and FDI inflows (Stevens, 1998); thus posits that
Hypothesis 7. Foreign Exchange Rates Uncertainty[3] Perception has a negative effect on Foreign Direct Investment (FDI) inflow

Although a clearer picture of what investment facilitation means has yet to be developed, facilitating FDI flows is essential to mobilizing resources for development. Governments are increasingly concerned with investment facilitation (Hees & Mendonça Cavalcante, 2017). Many countries have recognized the importance of focusing on domestic reforms in the area of investment facilitation to attract foreign direct investment, including regulatory transparency, streamlining administrative processes, and dispute prevention (International Centre for Trade and Sustainable Development, 2020).

A study that investigates private investment facilitation strategy finds that the primary mechanism to market or "sell" the State as a prime location for private sector investment would significantly impact FDI inflow if not because of its invisibility. The State does not typically appear on the long list of location alternatives for active consideration by investors (Effiom & Etim Edet, 2019). We, however, know that at the federal level, when the One-Stop Investment Center (OSIC) at Nigerian Investment Promotion Commission was established in 2006, it recorded an unprecedented influx of FDI inflows (Nigerian Investment Promotion Commission, 2017); thus, I posit that:
Hypothesis 8. Investment Facilitation Perception has a positive effect on Foreign Direct Investment (FDI) inflow.
The SEM hypothesis is depicted in Figure 1

Fig 1: SEM Model Hypothesis



B. Analysis for Structural Equation Modelling (Descriptive)

➢ *Measurement model.*

We conducted the case and variable screening (Yusuf, 2020) and then analyzed the factor loadings and cross-loadings of the items. As a rule, items were maintained if (a) they had high loadings on their primary factor. Typically, l >.30. And if (b) they had minimal cross-loadings on some other factor (i.e., cross-loadings were less than half of their primary loadings (Hinkin, 1998). Kaiser-Meyer-Olkin (KMO) statistic was.659 (Kaiser Meyer, 1970). The commonalities are acceptable; they are all above the minimum limit of 0.300 (Hair, Black, Babin, & Anderson, 2010). Bartlett's Test of Sphericity was significant (Chi-square = 4924.914with df = 171, p.<0.001), implying significant intercorrelations. The five components had a total variance of 71.245% (Hair et al., 2010). The total variance explained can be obtained in Table 1. For the final pattern matrix that integrates Cronbach's alpha and the percentage of variance explained, refer to Table 1

We find that the factor Cronbach's alphas are robust; Ease-of-Doing-Business is 0.959, Investment Promotion is 0.895, Social Desirability is 0.957, security is 0.841, and Foreign Exchange Rates is 0.804, respectively. The Correlation

[2] This implies that the quantum of FDI inflow to a host country coupled with finished manufactured products contribute to more influx of foreign currency into the host country which helps stabilize the exchange rates, and on the other hand, if the rates are allowed to be freely manipulated by the government of parallel market, then risk of escalating the rates become higher which affect the investor' decision to continue with investment or expansion.

[3] FOREX rate is a high risk factor associated with investment uncertainty, where sufficient exchange rate volatility usually increases expected profit.

Matrix Table was inspected in Table 2, with none of the amounts surpassing the threshold of 0.7 (Hair et al., 2010).

TABLE 1: Pattern Matrix Table with Cronbach's Alpha

Pattern Matrix					
	Factors - Select Dependent variables				
	Ease of Doing Business	Investment Promotion	Social Desirability	Security	Foreign Exchange Rates
Cronbach's Alpha Loadings	0.959	0.895	0.957	0.841	0.804
% of Variance Explained	22.825	14.789	14.22	11.836	7.575
EODB3	0.901				
EODB4	0.945				
EODB5	0.984				
EODB6	0.852				
Sec1				0.600	
Sec3				0.872	
Sec5				0.898	
Sec6				0.614	
Forex2					0.522
Forex3					0.779
Forex5					0.728
Forex6					0.803
InvPro2		0.768			
InvPro3		0.866			
InvPro5		0.878			
InvPro6		0.814			
SD2			0.940		
SD3			0.974		
SD4			0.903		

TABLE 2: Factor Correlation Matrix

No.	Factor	1	2	3	4	5
1	Ease-Of-Do-Business	1				
2	Security	0.134	1			
3	Foreign Exchange Rate	.030*	.105***	1		
4	Investment Promotion	.189**	.159**	0.019	1	
5	Social Desirability	0.078	0.184	0.01	0.334	1

Significance Indicators: $p < 0.100$, * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

We applied the pattern matrix obtained from the EFA to build a CFA model structure and then examined it with AMOS software v25.0. The sample size of 250 was adequate, and the commonalities were sufficient. For model fit, the chi-square CMIN value was 336.976 with 139.00 degrees of freedom, and CMIN/DF is 2.424, which is between 1 and 3 and, therefore, considered good. CFI=0.96, SRMR=0.060, RMSEA is 0.076, and the p-value was significant .000, indicating we can reject the null hypothesis as the model is statistically significant (Hair et al., 2010).

Composite reliability (C.R.) results for all the variables exceed the threshold of 0.7 (Hair et al., 2010), with ease of doing business at 0.965. I retained all. Convergent validity (AVE) values were >0.5 (MacKenzie, Podsakoff, & Podsakoff, 2011), with social desirability highest at 0.892. The constructs have excellent validity; all convergent validity (AVE) values are more significant than 0.5 (Mackenzie et al., 2011). Composite reliability (C.R.) scores for all the variables surpass the threshold of 0.7 (Hair et al., 2010), as shown in Table 3.

Table 3: CFA Model Validity Analysis

	CR	AVE	MSV	EaseOfDoingBus	InvestProm	SocDesir	Security	FOREXR
EaseOfDoingBus	0.965	0.873	0.051	**0.934**				
InvestProm	0.876	0.646	0.051	0.225**	**0.803**			
SocDesir	0.961	0.892	0.003	0.041	0.052	**0.944**		
Security	0.782	0.522	0.062	0.057	0.188**	0.039	**0.722**	
FOREXR	0.862	0.613	0.062	0.136	0.112	⁂	0.25	**0.783**

Significance Indicators: $p < 0.100$, * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$ Validity Concerns
⁂Correlation is not specified in the model. No validity concerns here

The chi-square difference test results indicate the unconstrained model, chi-square=576 DF=278, and another set of chi-squares from a completely constrained model (zero and equal; chi-square=600.5, DF=297). The p-value is significant; 0.040 significant; 0.040 significant; 0.040 significant; 0.040. The results suggest that we are 90% confident that Common Method Bias (CMB) exists. We now controlled the method bias by applying common method variance (CMV) or Common Latent Factor (CLT) statistical techniques.

➢ *Structural Analysis.*

We imputed the constructs centered on the final CFA model, which comprised method bias adjustment by integrating the unmarked variables of the CLF factor score in the imputed variables. The structural model combines computed variables (latent factors) following the CFA and calculated mean variables from the formative constructs. The analyzed research models for the study are depicted in Figure 1.

➢ *Multivariate assumptions.*

On linearity, the results imply some robust linear relationships between the variables with the highest "Fs." Still, the connections are significant; that is, p=.001, and the F value is the highest in the equation (10.860). For Ease of Doing Business to Investment Promotion and p=0.000, Return on Investment and Investment Promotion, they are sufficiently linear to be tested in covariance-based SEM algorithms. We did not observe VIFs greater than 3.1.

Cronbach's alphas (Tavakol & Dennick, 2011) suggest decent reliabilities of the reflective variables, as shown in the EFA earlier; refer to Table 5. We assessed the model fit and observed that the chi-square CMIN value was 21.6629, with 11.00 degrees of freedom. CMIN/DF is 1.9694, considered acceptable. CFI=0.9728 and, SRMR=0.0615, RMSEA is 0.0615. Pclose=0.274 and the p-value is 0.0274, which is significant (Hair et al., 2010) as shown in Table 4

Table 4: Model Fit

Measure	Estimate	Threshold	Citation
CMIN	21.6629	--	(Baumgartner & Weijters, 2017)
DF	11	--	(Baumgartner & Weijters, 2017)
CMIN/DF	1.9694	Between 1 and 3	(Baumgartner & Weijters, 2017)
P-Value	0.027	Significant	Hu, and Bentler (1999)
CFI	0.9728	>0.95	Hu, and Bentler (1999)
SRMR	0.0615	<0.08	Hu, and Bentler (1999)
RMSEA	0.0615	<0.06	Hu, and Bentler (1999)
P-Close	0.274	>0.05	Farooq, O., Rupp, D. E., & Farooq, M. (2017). Kline (2011)

We now created and analyzed the algebraic table containing the inter-correlations among the various study variables. The outcome suggests the statistical significance of the correlations at $p<0.01$ and $p<0.05$ in most independent variables except between Corruption and Investment Incentives; this is shown in Appendix G.

We have generated the underlying model using the Statistical Package for the Social Sciences (SPSS) and Analysis of Moment (AMOS) version 26 analytical tool. In the process, we uploaded eight exogenous FDI perception factors, control factors, and FDI endogenous factors from the variable data set. We then link the exogenous elements to the endogenous factors of FDI inflow and compute the estimates. We evaluated the direct effect by calculating the estimates and then examining the results to ascertain the model fit, regression weights, beta-estimations, p-values, and R-square. Years of Investment, Education, and Gender control FDI inflow decisions.

C. Machine Learning Models for Prediction

➢ *Source of dataset*

The source of this FDI dataset is described under the multilevel list number 4.2, and specifically, that of the target variable is depicted in Table 5

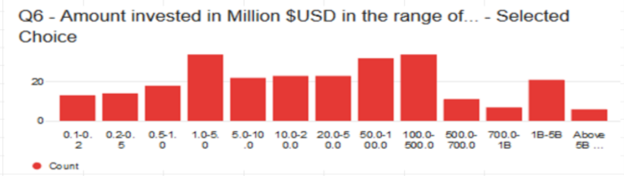
Table 5: Structure of Classified Data

Model A

FDI Inflow in monetary terms	
Investment from \$0.00 to \$500 M	Investments above \$500 M
Class 0	Class 1

Model B

FDI Inflow in monetary terms	
Class 1 - 13	



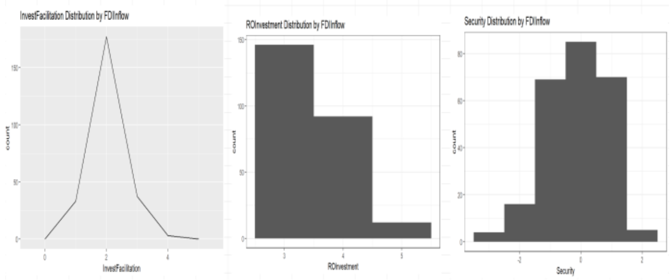
➢ *Logistic Regression (glm) Model*

Logistic regression is a model for binary classification predictive modeling. The parameters of a logistic regression model can be estimated by the probabilistic framework called maximum likelihood estimation (Brownlee, 2019). Logistic regression yields as good performance as ML models to make predictions, but it has been established that logistic regression, gradient boosting machines, and neural networks were systematically ranked among the best models (Simon Nusinovicia, 2020).

➢ *Naïve Bayes Model*

Naïve Bayes is a simple learning algorithm that applies Bayes' rules together with a strong assumption that the attributes are conditionally independent given the class. Naïve Bayes nonetheless often delivers competitive classification accuracy. Naive-Bayes is a generative model in which we model the conditional probability of input x given the label (Fred J. Damerau, 2010). We performed a couple of visualizations to take a better look at each variable before normalization, and this stage is essential to understanding the significance of each predictor variable, as depicted in Figure 2

Fig 2.: Visualized Data of a few variables



To predict using the Naïve Bayes algorithms, we ran the Naive-Bayes model and predicted the default status on the test set.

➢ *Decision Tree Model*

A decision tree is a type of Algorithm in machine learning that employs decisions as the elements to represent the result in the form of a tree-like formation. It is a graph that uses a branching method to illustrate every possible output for a specific input (Contributor, 2012).

To predict using "rpart" Decision Tree algorithms, we ran the Decision Tree model and forecast the default status on the test set using the ANOVA method. I plotted the tree with regular observation by setting the control part "min split" to 60 and predicting the FDI inflow classified amounts. To improve the model performance, We tuned the parameters to check if we could improve the model over the default value by controlling the min split to 4, "minbuckey" to round5/3, and max depth to 3. We anticipate an accuracy higher than 0.548.

- *K-Means (KNN) Model*

Machine learning techniques have been widely used in many scientific fields, but their use in the medical literature is limited partly because of technical difficulties. K-nearest neighbors (KNN) is a simple method of machine learning (Zhang, 2016)

K-Nearest Neighbor or K-NN is a Supervised Non-linear classification algorithm. K-NN is a non-parametric algorithm; i.e. Algorithm; i.e., it doesn't assume underlying data or its distribution. It is one of the simplest and most widely used algorithms, which depends on its k-value(Neighbors'-value)

We scaled the dataset and clustered the FDI inflow based on eight decision factors. The graph indicates the proximity of distance between related decision factors. Thereafter, we ran the k-means Algorithm to cluster the factors with the choice of the initial value of k = 4 and the number of restarts at 25.

A "train control()" function is used, and the "tune length" is set at 20 to select the optimal model and plot the outcome of repeated Cross-Validation with the application of RMSE. We scaled the data frame to obtain a z-score using the total Within the Sum of Square "wss" to determine the best number of clusters k. We now fitted the KNN model by training the FDI dataset using the function "knn" and generated the confusion matrix and ROC-AUC classifier. Before that, we evaluated the model to choose K with the best classification accuracy. We used K=1, 3. 5, and 15.

- *Random Forest, Bagging, and Boosting Trees*

A decision tree is a non-parametric supervised learning algorithm for classification and regression problems. It is also often used for pattern analysis in data mining. A decision tree works well with data without much preprocessing. It can use categorical values and numerical values as it is. It can also handle missing features and large-scale differences among different components in the dataset (Ping, 2022)

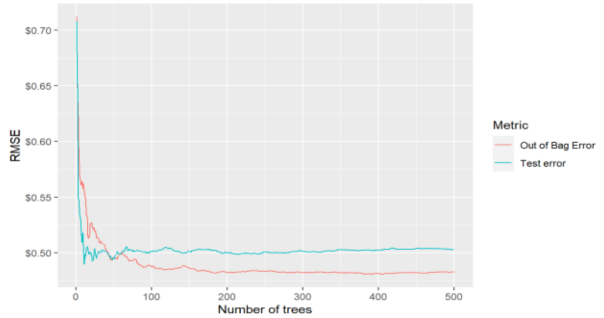
- *Bootstrap Aggregation (Bagging):*

This general procedure can be used to reduce the variance for algorithms with high variance by first selecting random samples of a training dataset with a replacement. The FDI decision classification could make predictions from this weak learner, combined to make a single prediction. This process of creating new FDI inflow bootstrap samples, fitting, and adding trees to the sample is repeated k times until no further development is seen in the ensemble's performance on a validation dataset. This results in better performance than a single well-configured decision tree algorithm.

- *Random Forest:*

To have an attribute with the highest information gain and split based on decision attributes, a high-performant ensemble model with a sufficiently diverse group of individual base learners, we applied random forest with a penalty when the trees start to pick a particular attribute at a given level more than certain times. Random Forest models decide where to split based on a random selection of features, unlike bootstrapped, whose data broadly breaks off at the same features throughout each model. We performed a random forest tuning with the use of OOB so that R.F. could be fit in one sequence, with cross-validation so that once the OOB error stabilizes, the training can be terminated. We now created the training and validation datasets, then extracted an OOB & validation errors, and compared the error rates by changing the number of trees and with different vi as indicated in Figure 3.

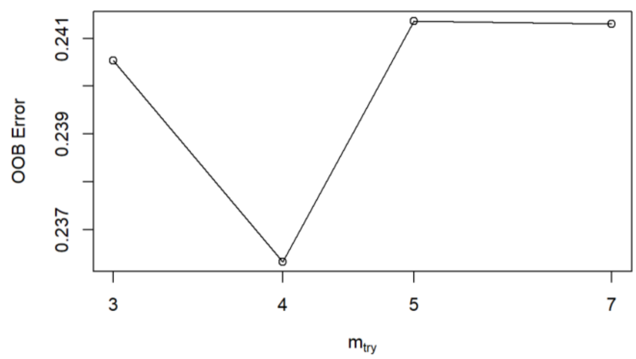
Fig 3: Error Rates by Trees number
Result:



More trees are generally better in performing rf so long as we can support training the Algorithm. The classification error is lowest with Out-of-Bag Error.

The hyperparameters of the random forest model are searched for using the Out-Of-Bag (OOB) errors. Recall that the number of attributes selected randomly at each split node indicates that the optimal value of the m parameter "mtry" is four, as depicted in Figure 4

Fig 4: Out-Of-Bag (OOB) errors



We searched for a hyperparameter grid by attempting different values of hyperparameters of "mtry" values between 20 to 30 in step of 2 for the ranger model. The combination of these hyperparameters creates a grid search with a size of 96. By measuring the model prediction error for each combination, I find the index combination that results in a minimum OOB RMSE where "mtry" is set to 28, the node size is 3, and 80% of data is sampled during the bagging process.

We make FDI inflow classification investment decisions on the Ada Boost dataset. The number of trees is specified using the" iter" parameter, which is set to 500 in this study.

- *Neural Network*

Typical neural networks, which are the basis of "deep learning" approaches, use many layers of interconnected neurons that transform the complex, high-dimensional input signal into a classification or regression output (Rifai, 2022). Using the "neural net, "we regressed the dependent variable "FDI inflow" variable against the other independent variables and set the number of hidden layers to (2,1) based on the hidden (2,1) formula.

The linear output variable is set to FALSE, considering the impact of the independent variables on the dependent variable is assumed to be non-linear. I also set the threshold to 0.01, connoting that if the change in error during an iteration was less than 1%, then no additional optimization would be carried out by the model. Applying a (2,1) configuration yielded 0.629% classification accuracy for this model

We then generated the error of the neural network model, along with the weights between the inputs, hidden layers, and output. We now predicted the rating using the neural network model. The expected rating would be scaled and transformed to make a logical comparison with the actual rating. Sequel to that, we created a confusion matrix to compare the number of true/false positives and negatives.

- *Gradient Boosting*

Boosting is a sequential technique where each new model is built from learning the established errors of the previous model, i.e., each predictor is trained using the residual errors of the predecessor as labels.

Boosting, which is analogous to the bagging method, except the trees are grown sequentially: each succeeding tree is developed using information from earlier grown trees to minimize the error of the earlier models.

D. Forecasting FDI Inflow Decision with ARIMA

ARIMA is the abbreviation for Autoregressive Integrated Moving Average. Auto-Regressive (A.R.) terms refer to the lags of the difference series; moving Average (M.A.) terms refer to the lags of errors and are the number of differences used to make the time series stationary.

In model A of this ARIMA model, We used classified "0" as the investments made by investors before 2006 to 2018, which range from $0.00 M to above $6B, and classified "0" as investments of up to $500, whereas "1" represents the investments made from $500 and above. In model B, the investments are classified as classes 1 to 13 in Billions of USD, as depicted in Table 5 above. To get better results, we have normalized the datasets in the two ARIMA models (Date exclusive) with the use of the "range" method to ensure it represents a data frame.

- *Time Series Stationary:*

To perform any successive modeling on the FDI time series, our time series must be stationary; that is, the mean, variance, and covariance of the series should all be constant with the given time. We also converted the data frame to time series and double-checked with the Dickey-Fuller Test of Stationarity, using the relevant packages to plot the "acf", "pacf", and the "adf." ACF stands for Auto-Correlation Function. ACF gives us values of any autocorrelation with its lagged values. In essence, it tells us how the present value in the series is related in terms of its past values. PACF stands for Partial Auto-Correlation Function. Instead of finding correlations of the present with lags like ACF, it finds a correlation of the residuals with the next lag value.

IV. RESULTS

A. Hypothetical Model Results for SEM

Our findings indicate that the hypotheses; Return on Investment has a positive effect on FDI inflow (β= 0.9819, P=0.0306 **) (H1c), and Security/Personal Safety Perception has a negative influence on FDI inflow (β= –0.4902, 0.0187**) (H1). And Investment Facilitation Perception has a positive effect on FDI inflow (90%, β= 1.0465, 0.03575**) These are supported with significant P-Values <0.05. Nevertheless, the other theories (H1a, H1b, H1d, H1f, and H1g) are not supported. Even though the measurements were not statistically significant, they were positive.

These results also suggest the strongest (95% Confidence Interval) meaningful relationships among the Variable quantities of ROI on FDI inflow decisions (95%, □=□0.9819), Security on FDI inflow decisions (95%, □= 0.4902), and Investment Facilitation on FDI inflows (90%, □= 1.0465). Refer to Figure 5 and Table 6 for results.

Figure: 5: SEM Analysis Result

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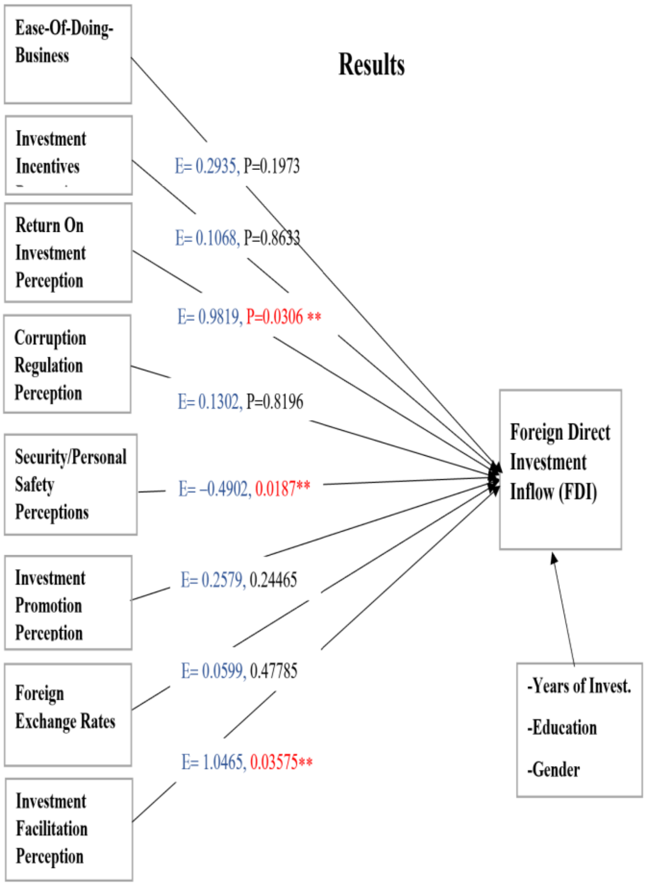


Table: 6: Summary of Hypotheses Test (Descriptive Analysis)

Direct Effects	Predictor	Hypothesis supported?	Regression Weight (Betas) - Estimates(Betas) - Estimates	Significance (P-values)
H1: Ease-Of-Doing-Business Perception has a positive effect on Foreign Direct Investment (FDI) inflow	Ease-Of-Doing-Business	No	0.2935	0.1973
H2: Investment (Business) Incentives Factor has a positive effect on Foreign Direct Investment (FDI) inflow	Investment (Business) Incentives	No	0.1068	0.8633
H3: Return on Investment Perception has a positive effect on Foreign Direct Investment (FDI) inflow	Return on Investment	Yes	0.9819	0.0306 **
H4: Corruption Perception has a negative effect on Foreign Direct Investment (FDI) inflow	Corruption	No	0.1302	0.8196
H5: Security/Personal Safety Perception has a negative effect on Foreign Direct Investment (FDI) inflow Factor	Security/Personal Safety	Yes	-0.4902	0.0187***
H6: Investment Promotion has a positive effect on Foreign Direct Investment (FDI) inflow	Investment Promotion	No	0.2579	0.2446
H7: Foreign Exchange Rates uncertainty has a negative effect on Foreign Direct Investment (FDI) inflow	Foreign Exchange Rates Manipulations	No	0.0599	0.4778
H8: Investment Facilitation Perception has a positive effect on Foreign Direct Investment (FDI) inflow	Investment Facilitation	Yes	1.0465	0.0357

B. Machine Learning model Results

➢ *Logistic Regression (glm) Model*

Table 7: Significance of the Variables

Coefficients

	Estimates (Beta)	Std.Error	Z-value	Probability
Most Significant Variables: (Dependent Variables)				
Investment Facilitation	2.3205	1.1832	1.961	0.0498*
Return-On-Investment	2.0022	0.8797	2.276	0.0228*
Investment Promotion	1.5771	0.7934	1.988	0.0468*

Deviance Residuals:	Min: -1.7586, 1Q: -1.2037, Median: 0.7556, 3Q: 1.0497, Max: 1.5089
Signif.Codes:	0 "***", 0.001 "**", 0.01 "*", 0.05 ".", 0.1 "". 1

We can see from R-generated Table 6 that Security, Ease-Of-DoingBus, Corruption, Investment Incentives, Investment Incentives, and FOREX are not statistically significant. As for the statistically significant variables, Return-On-Investment has the lowest p-value suggesting a strong association of the ROI with the probability of having an FDI inflow decision. The negative coefficient for this predictor indicates that all other variables, being equal, security and corruption, are less likely to have influenced FDI inflow decisions.

In the output above, the first thing we notice is the call; this is R reminding us what the model we ran was and what options we specified. Deviance residuals are a measure of model fit. This part of the output shows the distribution of the deviance residuals for individual cases used in the model.

For every one-unit change in InvestFacilitation, the log odds of FDI inflow in \$0-\$500m (versus above \$500m) increases by 2.0022.For a one-unit increase in ROI, the log odds of FDI inflow in \$0-\$500m (versus above \$500m) increase by 1.7311.

For a one-unit increase in Investment Promotion is, Promotion, the log odds of FDI inflow in $0-$500m (versus above $600m) increases by 1.5771.

The ANOVA test is performed, and the difference between the null and residual deviance depicts how the model is doing against the null model (a model with only the intercept). The more significant this gap, the better it becomes. There is a drop in deviance when we add each variable one at a time.

Besides, increasing ROI and Investment Promotion factors significantly reduce residual deviance. The other variables seem to improve the model less. This is depicted in Appendix H.

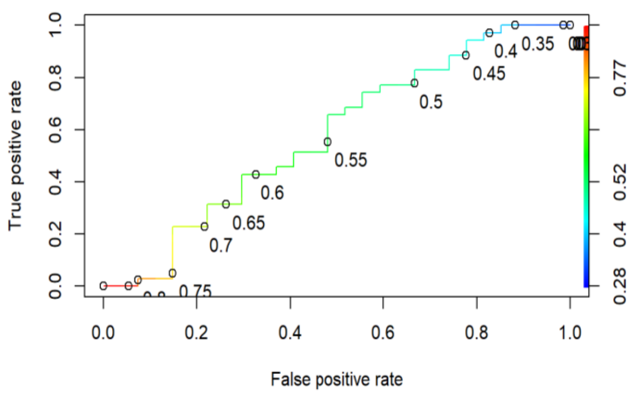
In making a prediction, we used "FDI_rf_model_glm" to assess the predictive ability.

We evaluated the fitting of the model to determine how the model is doing when predicting you on a new set of data by setting the parameter type "response" with the expectation that R would output probabilities in the form of P(y=1|X). Our decision boundary would be 0.5 with the condition that if P(y=1|X) > 0.5, then y = 1; otherwise, y=0.

We now plotted the ROC curve and calculated the AUC (area under the curve), which are typical performance measurements for a binary classifier

We also checked on the model misclassification. Misclassification errors came out to be 41.93%. We could use regression techniques with categorical variables to compare various other data. Although, as a rule of thumb, a model with a sound predictive ability should have an AUC closer to 1 (1 is ideal) than 0.5; this, and any other models, ranging from 0.52 to 0.63 because more than half of the dependent variables don't have a significant P-value. We changed the parameters to improve the AUC of this model from 0.5524 to 0.5767.

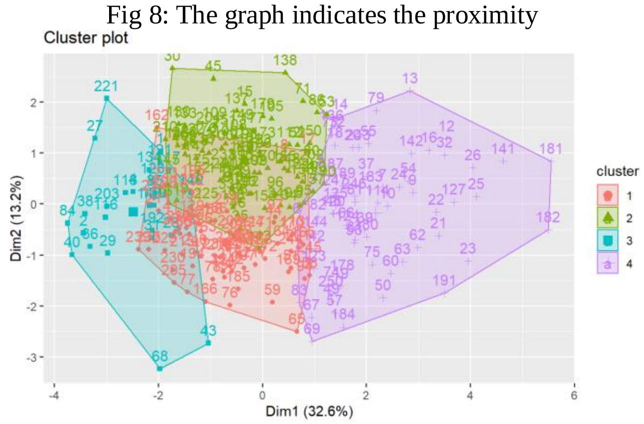
Fig 6: AUC for Changed Parameter



In the graph, the x-axis is the false positive rate, and the y-axis is the true positive rate. We can see each of the points represents a confusion matrix that we don't have to evaluate manually. The points also represent the tradeoff between true positive and false positive, as depicted in Figure 7. ROI has the lowest p-value suggesting a strong association of the ROI with the probability of having an FDI inflow decision, and by increasing ROI and Investment Promotion factors, the residual deviances are significantly reduced. AdditionallyAlsoAdditionally, changing the parameter improves the predictive power of the model (AUC)

➢ *K-Means (KNN) Model*

Fig 8: The graph indicates the proximity



We now have 4 clusters of variables

We now re-ran the Algorithm using other distances. We obtained a new cluster size which indicates the cluster of the 250s observations in the combinations of 73, 84, 26, and 67. ResaM.pling results across tuning parameters used k=11 to obtain the minimal (best) RMSE of 0.4772065

Table 8: Resampling minimal RMSE error

k	RMSE	Rsquared	MAE
5	0.5047753	0.09424912	0.4255556
7	0.4918104	0.09898057	0.4358535
9	0.4775780	0.12332118	0.4338532
11	0.4772065	0.12776931	0.4400053
13	0.4784726	0.11961181	0.4463085
15	0.4824191	0.10536573	0.4538101
17	0.4809633	0.10905268	0.4552103
19	0.4841831	0.09581235	0.4610575
21	0.4861888	0.08853318	0.4649097
23	0.4873652	0.08682013	0.4677918
25	0.4869023	0.09661050	0.4684903
27	0.4840764	0.09677520	0.4668050
29	0.4845893	0.09488967	0.4678658
31	0.4839431	0.09746337	0.4683732
33	0.4847006	0.09379764	0.4702465
35	0.4851528	0.08753375	0.4717292
37	0.4865247	0.09236476	0.4737180
39	0.4882967	0.08496160	0.4764290
41	0.4890632	0.07700732	0.4774035
43	0.4906839	0.06816758	0.4792674

The chart shows that elbow point 2 provides the best value for k. While WSS will continue to drop for larger values of k, we have to make the compromise between overfitting. Here, the elbow point provides that compromise where WSS, while still decreasing beyond k = 2, drops at a much lower rate. In other words, adding more clusters beyond 2 brings less improvement to cluster homogeneity

To confirm that, we also applied the Silhouette Method to determine the number of clusters. Again, we see that 2 is the ideal number of clusters. Here we look for large values for the Silhouette Width (Y-Axis)

Fig 9: The best K with WithiN.N.N. Sum of Square "wss"

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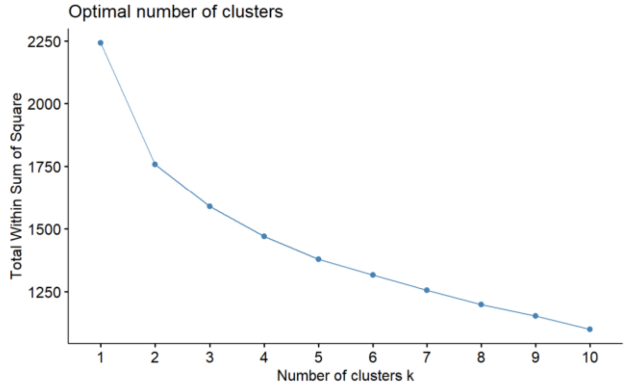
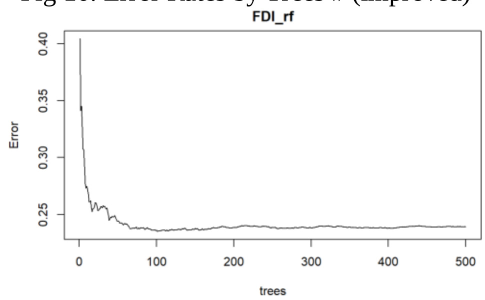


Alternatively, I applied the Silhouette Method to determine the number of clusters. Again, we see that 2 is the ideal number of clusters. Here we look for large values for the Silhouette Width (Y-Axis). K= 3 has the best accuracy and so fitted the KNN model with K at three and generated confusion Matrix and ROC-AUC. The summary of accuracy metrics is shown in Table 14

➢ *Random Forest, Bagging, and Boosting Trees*

It can be seen that the random forest model has 500 trees, which is the default setting, and two variables were tried at each split; it is our m parameter. The model seems to have a relatively low R-squared value of 2.28% because a few variables out of eight have significant p-values. The plot of the training error rate against the number of trees indicates a considerable improvement for adding the first 100 trees and virtually a flat error rate after that, as shown in Figure 10.

Fig 10: Error Rates by Trees # (improved)



The MSE is at its minimal when the number of trees is 101, and the RMSE of this optimal random forest is 0.4849.0.4849.

The confusion matrix output classified eight false positives and 17 false negatives. A summary of the result is depicted in Table 26 and ROC-AUC in Appendix P

➢ *Neural Network*

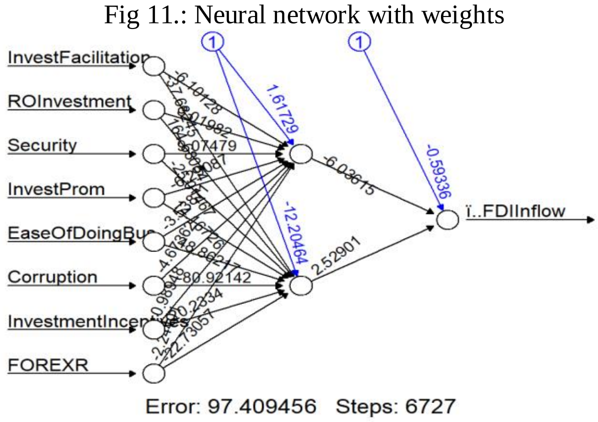
Given the output, we may conclude that both repetitions converge. However, we will use the output driven in the second repetition because it gives less error (97.40946) than the error (100.43106) from the first repetition derives. We now generate the error of the neural network model, along with the weights between the inputs, hidden layers, and outputs, as shown in Table 28 and Figure 16

Table 10: Error of the neural network

Result:

```
                                          [,1]          [,2]
error                              1.004311e+02  9.740946e+01
reached.threshold                  9.687668e-03  9.970533e-03
steps                              1.152600e+04  6.727000e+03
Intercept.to.1layhid1              6.843757e+00  1.617293e+00
InvestFacilitation.to.1layhid1    -6.415067e+00 -6.101275e+00
ROInvestment.to.1layhid1          -2.842402e+00  3.019823e+00
Security.to.1layhid1               3.843690e+00  9.074793e+00
InvestProm.to.1layhid1             3.181185e+00 -6.290869e+00
EaseOfDoingBus.to.1layhid1        -4.160448e+00 -3.538714e+00
Corruption.to.1layhid1             2.791602e-01 -4.673621e+00
InvestmentIncentives.to.1layhid1  -3.511330e+00  9.894773e-01
FOREXR.to.1layhid1                -2.724015e+00 -2.244012e+00
Intercept.to.1layhid2             -2.499559e+01 -1.220464e+01
InvestFacilitation.to.1layhid2    -4.346536e+01 -3.768245e+01
ROInvestment.to.1layhid2           6.884350e+01  1.646805e+02
Security.to.1layhid2               7.089692e+00 -2.501467e+01
InvestProm.to.1layhid2             1.137413e+02  1.416726e+01
EaseOfDoingBus.to.1layhid2        -2.604995e+01  4.886217e+01
Corruption.to.1layhid2             4.121590e+00 -8.092142e+01
InvestmentIncentives.to.1layhid2  -2.594828e+01  2.023340e+01
FOREXR.to.1layhid2                -3.807457e+01 -2.273057e+01
Intercept.to.ï..FDIInflow          2.736763e+00 -5.933644e-01
1layhid1.to.ï..FDIInflow          -5.979972e+00 -6.036152e+00
```

Fig 11.: Neural network with weights



It can be seen that each predictor variable has one neuron. The first layer has eight neutrons. The second layer has two neurons, and the out variable has one neuron.

The model generates seven true negatives (0's), 31 true positives (1's), and 27 false positives (0 s), while there are 17 false negatives. Ultimately, we yield an 54.84% accuracy rate in determining whether an FDI investment decision is above $600m or not, with an AUC of 0.5013. The misclassification error came out to be 13.67%. We can further increase the accuracy and efficiency of our model by increasing or decreasing nodes and bias in hidden layers. The strength of machine learning algorithms lies in their ability to learn and improve every time in predicting an output.

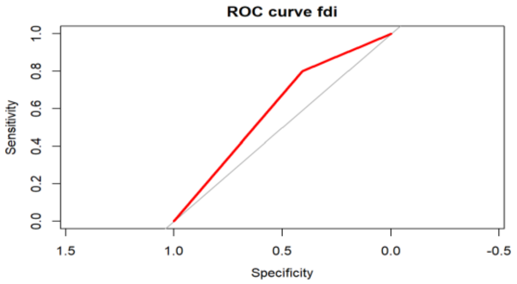
➢ *Gradient Boosting*

The predicted numbers using six trees are shown in Table 11

Table 11.: Predicted numbers

	Prediction on six trees	
No.	0	1
1	0.52640831	0.4735917
2	0.04843777	0.9515622
3	0.1382829	0.8617171
4	0.13219363	0.8678064
5	0.18889204	0.811108
6	0.40360853	0.5963915

Fig 12.: ROC-AUC for Gradient Boosting



Of the variables, FOREX, Security/safety, and Ease off-Doing-Business are on top of the list

- *Decision Tree Model*

Security has the highest variable importance, as depicted in Table 12.

Table 12: Split errors and Variable Importance

```
          CP nsplit rel error    xerror       xstd
1 0.05596186      0 1.0000000 1.012532 0.01734865
2 0.03573464      2 0.8880763 1.134537 0.06176648
3 0.03497256      5 0.7808723 1.156479 0.07348537
4 0.02767599      6 0.7458998 1.157036 0.08051876
5 0.02529032      9 0.6572090 1.227509 0.09066205
6 0.02498334     10 0.6319187 1.289798 0.09682921
7 0.02167742     11 0.6069353 1.287232 0.09794442
8 0.02007168     12 0.5852579 1.288497 0.10028791
9 0.01000000     13 0.5651862 1.262434 0.10129450

Variable importance
            Security  InvestFacilitation  InvestmentIncentives
                  24                  18                    13
          InvestProm         ROInvestment        EaseOfDoingBus
                  12                  12                     9
              FOREXR           Corruption
                   7                   5
```

We tried to tune the parameters and see if we could improve the model over the default value. But need to get an accuracy higher than 0.548. We now have an improved variable of importance with the controlled part, as shown in Table 13.

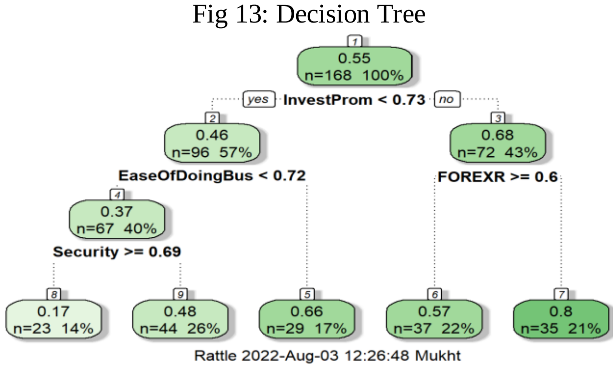
Table 13: Split errors and Variable Importance (improved)

```
          CP nsplit rel error    xerror       xstd
1 0.05596186      0 1.0000000 1.012532 0.01734865
2 0.04833315      2 0.8880763 1.049315 0.03744332
3 0.02929401      3 0.8397431 1.100830 0.06145950
4 0.00000000      4 0.8104491 1.147046 0.07723113

Variable importance
          Security          InvestProm InvestFacilitation              FOREXR
ROInvestment
                38                  35                 23                   3
2
```

From the tree, it is clear that those who have an Investment Promotion decision of less than 0.73, Ease of Doing business of less than 0.72, and Security decisions equal to or greater than 0.69 are those that invested in more than $500m, as depicted in Figure 13

Fig 13: Decision Tree



- *Naïve Bayes Model*

The first part of the output above shows the ratios of FDIInflow above $500m (yes) and FDIInflow below $500 m (no) in the training set (called a priori probabilities), followed by a table giving for each target class, mean and standard deviation of the (sub-)variable. Also, note that the Naive Bayes algorithm assumes a normal distribution for the independent variables using numeric predictors. The conditional probabilities for each attribute level given the FDIInflow status are missing because all the predictors are non-categorical.

The AUC and Accuracy of the model are not that strongly in tune with the model's algorithms and the predictors' significance.

C. Consolidated Results Summaries

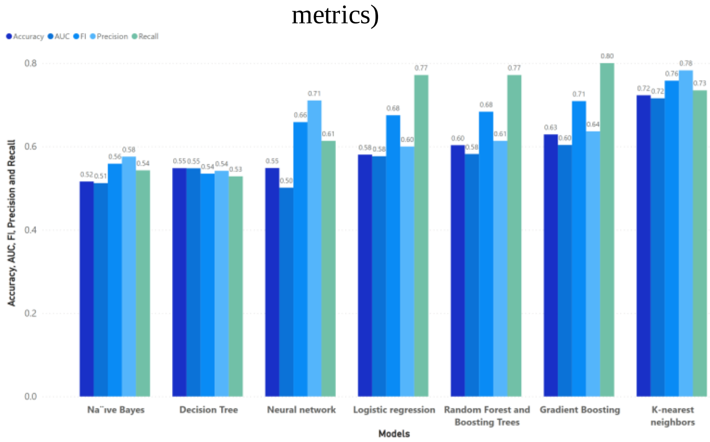
Table 13: Consolidated summary of other ML models

Other Models

Models	AUC	Accuracy	FI	Precision	Recall
Lasso-Ridge Regression					
Na¨ive Bayes	0.5122	0.5161	0.5588	0.5758	0.5429
Random Forest and Ada Boost	0.5821	0.6032	0.6835	0.6136	0.7714
Neural network	0.5013	0.5484	0.6585	0.7105	0.6136
Logistic regression	0.5767	0.5806	0.675	0.6	0.7714
Decision Tree	0.5478	0.5481	0.535	0.5417	0.5285
K-nearest neighbors	0.7156	0.7229	0.7579	0.7826	0.7347
Gradient Boosting	0.6037	0.629	0.7089	0.6364	0.8

We now used Tableau to visualize the summary of all other ML models (Accuracy only) and the combined metrics result (AUC inclusive) as depicted in Figure 14

Fig 14.: Visualized summary of other ML models (combined metrics)

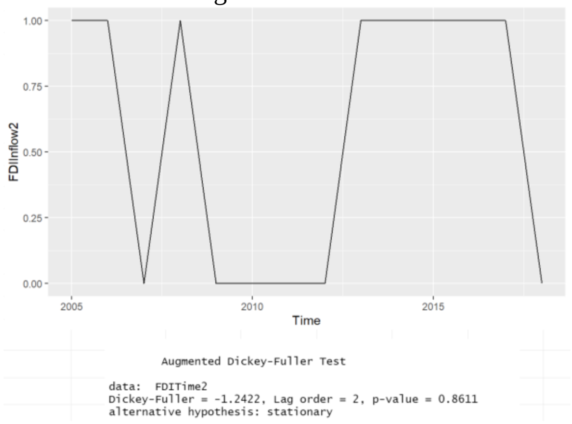


Analysis of the models indicates that at 0.72, K-nearest neighbors had the highest accuracy and were 40.07% higher than Naïve Bayes, which had the lowest accuracy at 0.52. Accuracy and total AUC are positively correlated with each other. K-nearest neighbors accounted for 17.43% of accuracy. Across all 7 Models, Accuracy ranged from 0.52 to 0.72, AUC ranged from 0.50 to 0.72, and F.I. ranged from 0.54 to 0.76.

The visualization suggests that Random Forest and Ada Boosting Trees have effective classification accuracies despite the context of "the No free lunch" theorem

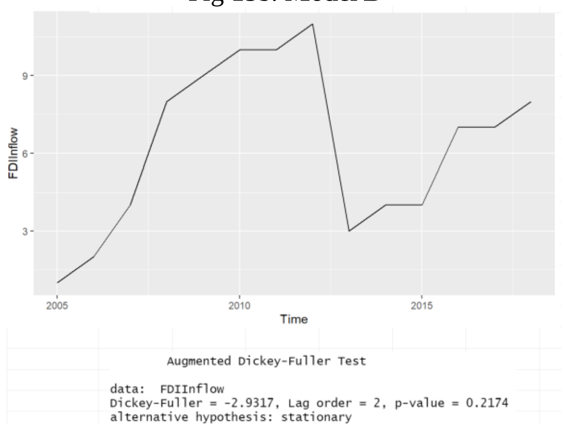
D. Forecasting FDI Inflow Decision with ARIMA

Fig 15a: **Model A**



In model A, the ACF of the residuals shows no significant autocorrelations, as shown in Appendix P. Even after conversion, the data remains stationary, with no difference after being controlled. The Dickey-Fuller test returns a p-value of 0.8611, resulting in the rejection of the null hypothesis and accepting the alternative hypothesis that the data is stationary, as shown in Figure 15b

Fig 15b: **Model B**



In model B, the ACF of the residuals shows no significant autocorrelations. After conversion, we have improved stationary data, with no difference after being controlled. The Dickey-Fuller test returns a p-value of 0.2174, as in Figure 21, resulting in the rejection of the null hypothesis and accepting the alternative hypothesis that the data is stationary, as shown in Appendix Q.Q. The two outputs have fluctuating patterners but are stationary with P-values of more than 0.05, so we checked the best model

➢ *Choice of best models*

To create an FDI model, we used the "auto. Arima()" function in R that uses a combination of unit root tests and minimization of the AIC and MLE to obtain an ARIMA model. The best ZRIMA in model A is ARIMA(0,0,0), and in the model, B is ARIMA(1,0,0), as shown in Table 15

Table 15: ARIMA(0,0,0) and ARIMA (1,0,0)

Model A

ARIMA Model	Mean type	Mean
(2,0,2)	Non-Zero	Inf
(0,0,0)	Non-Zero	24.03349
(1,0,0)	Non-Zero	25.43414
(0,0,1)	Non-Zero	25.56583
(0,0,0)	Zero	33.89566
(1,0,1)	Non-Zero	27.38972

Coefficient mean = 0.5714
AIC = 24.03
AICc = 25.12

Best Model: ARIMA (0,0,0) with Non-Zero

Model B

ARIMA Model	Mean type	Mean
(2,0,2)	Non-Zero	Inf
(0,0,0)	Non-Zero	75.6486
(1,0,0)	Non-Zero	71.9724
(0,0,1)	Non-Zero	73.6305
(0,0,0)	Zero	96.2972
(2,0,0)	Non-Zero	73.2946
(1,0,1)	Non-Zero	73.7237
(2,0,1)	Non-Zero	Inf
(1,0,0)	Zero	73.1562

Coefficient mean = 5.9466
AIC = 71.79
AICc = 74.37

Best Model: ARIMA (1,0,0) with Non-Zero

After converting the data and then checking the partial A correlation function, We confirmed that the ACF of the residuals shows no significant autocorrelations.

➢ *FDI decisions Prediction*

Now we make a forecast at 95% CI and forecast for ten years using the ARIMA Model as depicted in Figures 16a and 16b.

Fig 16a: Forecast for 10 Years
Results:

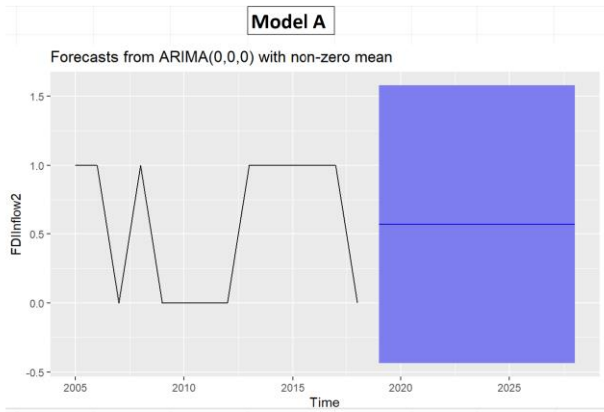
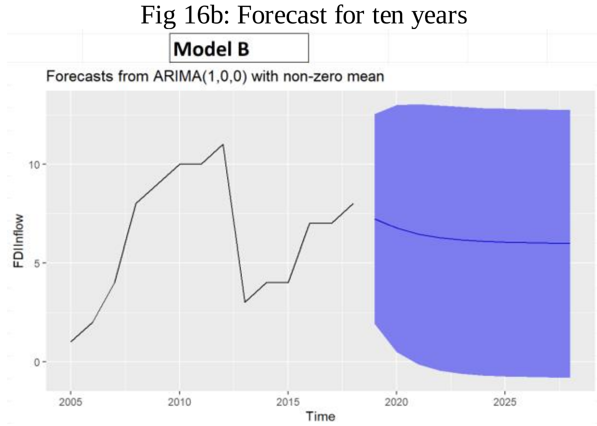


Fig 16b: Forecast for ten years



The forecasts are shown as a blue line, with the 80% prediction intervals as a dark-shaded area and the 95% as a light-shaded area. Validate the forecast with "Box. Test" to check if there are correlation problems. We checked with lags 2, 5, and 7. None of the results is significant, i.e..,>0.05, indicating no correlation issues. This is illustrated in Appendix R

We now look at the residuals of the model. The residuals will tell us if the model was able to capture all of the information provided by the data. Three graphs, one story: 1) Time Series graph of the residuals, 2) ACF Graph for the first five lags, 3) Distribution of the residuals

For model A, the model left information in the residuals. The first and last graphs show us that the residuals don't appear to be in significant white noise but have some correlation among them, and the second graph confirms it. None of the first four lags go above the threshold established by the autocorrelation function.

For model B, the first and last graphs show that the residuals don't appear to be in significant white noise but have some correlation, and the second graph confirms it. None of the first five lags go above the threshold established by the autocorrelation function.

We analyzed time series on the FDI inflow decisions modeling in R. We dwelled on how to "rationalize" our data, determine order parameters from ACF/PACF, and ultimately how to build our ARIMA model and make a prediction with the two models. Time series modeling is a complex aspect, especially in the context of FDI decisions that determine the level of investments.

From the results, we may infer that:

- *An all-inclusive set of specific factors.*

We found considerable differences in individual experiences of the institutional environment, beneficial business environment, and safety concerns for FDI decisions. Some of these factors have a peculiar influence on various Machine Learning Models in terms of classification accuracy. The fewer the number of significant variable predictors, the weaker the predictive efficacy

- *Distinctive internal algorithms designed for each model*

Although the "No Free-Lunch theorem" states that all optimization algorithms perform equally well when their performance is averaged across all possible problems, this implies that there is no single best optimization algorithm; we discover that specific models have the potential to make a more accurate prediction on individual FDI decisions depending on the efficacy and size of the data collected. This also answered our first question.

- *The effect of the Length of Target classification*

The length of the vector class plays a critical role in determining its predictive efficacy, such that the longer/number of the categories of the target variable, the more feasible and better the effectiveness of its forecasting ability. However, in the quest for the accuracy of any predictive models, when researchers provide themselves with the correct data, they are sure to have a clearer view of the future, leading to more effective use of resources.

V. CONCLUSIONS – DISCUSSIONS

A. General

Investment decision-makers always quest to predict the values of foreseeable foreign direct investment and its foremost factors to ascertain its needs for the funding required for investment in general on the one hand and, on the other hand, to identify the approaches of attracting the beneficial FDI to the host country. In this study, we used machine learning algorithms to predict potential investors' foreign investment inflow decisions and their fundamental determinants. Sequel to using numerous algorithms for accuracy tests, it appears that the foreign direct investment inflows into Nigeria for the next decade, 2018–2028, would be on the decline, especially given the insecurity challenges.

This study addresses fundamental problems related to forecasting inflows of FDI based on individual decisions and to better understand the efficacy of ML models for making such decisions on multi-classes of investments. To this end, we attempted to gain a deeper understanding of how individual ML models predict FDI decisions.

To this end, we ventured to gain a deeper understanding of how individual perceptions drive FDI decisions and, more importantly, how the role of ML models in FDI inflow forecasting. We have addressed the two researched questions (1) To what extent do significant FDI decision factors contribute to determining the choice of the best A.I. model for prediction, and (2) How and to what extent does the class size of the target FDI decision variable determine its predictability?

On question (1), the findings support the hypothesis that; Return on Investment has a positive effect on FDI inflow, and Security/Personal Safety Perception negatively influences FDI inflow. And Investment Facilitation Perception has a positive effect on FDI inflow and is supported by significant P-Values <0.05. Nevertheless, the other theories (H1a, H1b, H1d, H1f, and H1g) are not supported.

With regards to question (2), given the ARIMA with models A and B, it is suggested that model B, with 13 different classes of the FDI target variables (compared to just 2), has a higher AIC, BIC. And Dickey-Fuller test returns a p-value which signifies a more reliable prediction/forecast.

We now know that the research questions have shaped the purpose of our study and formed the methods and the design of our analytics. Further to analytics of various ML models in the contexts of the "No Free-Lunch theorem," the ensemble method can be applied and often performs much better than any single classifier.

B. Summary of Conclusions - Practical Implication

These findings imply that the main FDI decision drivers and other key stakeholders have to look inwards to identify other significant individual FDI determinants to make more effective predictions of what FDI inflows within the next decade would be like. The ROC-AUC, Accuracy, and other metrics established under this study indicate average results (0.5 to 0.6). Still, ideally, it should be over 7.0.

The concerned IPAs in the African Sub-Region should empower and dedicate various R&D units to use the latest dataset and ML software for business analyses for a better FDI policy.

IPAs must be innovative to attract beneficial FDIs to their regions. For IPAs to perform effectively in this 21st century, while they hold onto the status quo, they must transform from investment intelligence to investment analytics with a view to making predictions.

With a number of Sub-Saharan African countries having electricity infrastructure challenges, among others, it is important that IPAs predict a surge or plummet in electricity generation and transmission investment projects by enhancing the enabling environment to attract FDI. For example, recently, in August 2021, global foreign direct investment (FDI) announcements surged as software and financial firms expanded their international footprints, and renewable developers outlined major green electricity generation projects. Strategic collaborations among the key FDI stakeholders and between academia and industry are highly suggested to achieve effective investment synergy.

We now also know that this study contributes to the literature on individual FDI decisions and economic growth. The importance of integrating investment promotion with investment facilitation has the potential to attract potential and existing investors from targeted regions. We suggest that FDI policymakers will find a modern-day scholarship, especially the application of A.I. more-and-more-helpful when they employ the method across the board for informed decisions and policymaking.

C. Limitations of the Study

We have a limited number of observed data in size and independent variables. In predicting FDI inflows based on investment decisions, we lacked monthly, quarterly, and semi-annual data, so we were left with no options but to use yearly data in the study. We had challenges generating a confusion matrix for some models because of their design or internal structures. In designing the model layout using Analysis of Moment (AMOS) for assessing the direct impact of the I.V.s on DV, we had to use a surrogate variable, "Business Environment," as a mediator for "FOREX" to get a good model fit.

D. Future Research

Our proposed future research would use quarterly preexisting FDI time-series data (to boost the number of observations) and also explore the effect of FDI decisions in some economic sectors bordering on manufacturing, entertainment, and services sectors. It is anticipated that future research should also integrate other predictor variables that were missing in this empirical stud

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