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Research Article

An Exploratory Machine Learning Analysis of Infrastructure Approval Drivers in Nigeria

*[1]Victor Oladoyin Shodipo, [1]Ogooluwa Philip Ojo, [1]Tope Akinfolarin Akintola, [2]Samuel Adedayo Ogundele, [1]Victor Oluwakayode Maku, [3]Boluwatife Ade-Akingboye, [4]Olayinka Victoria Shodipo

About Article

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About Author

[1] Sustainability Operation Initiative for Africa (SOI-AFRICA), Nigeria

[2] Jilcon Engineering Services Limited, Uyo, Nigeria

[3] Orion Consulting Engineering Services, Nigeria

[4] Department of Civil Engineering, Olabisi Onabanjo University, Olabisi Onabanjo University, Nigeria

Contact @ Victor Oladoyin Shodipo
shodipovictor100@gmail.com

ABSTRACT

Infrastructure projects are important to Nigeria's socioeconomic development. However, the basis for selecting, implementing, and commissioning such projects often remains unclear. Using a limited dataset of 30 projects in Nigeria between 2019 and 2024, this study employs expert-rated evaluations and machine learning to explore the underlying drivers of infrastructure approval. Projects were evaluated across categories, including economic impact, social value, safety, environment, technological advancement, and political biases. A Random Forest Model trained on expert ratings achieved 67% accuracy, with economic impact and safety enhancement emerging as the most influential decision factors. The analysis revealed critical approval thresholds, where projects scoring below moderate influence (3.0) on economic impact had less than a 45% likelihood of approval. Notably, while political bias received low expert ratings, it significantly reduced approval probabilities when present. The study introduces practical innovations for systematically comparing expert assessments with data driven driver weights and an interactive tool for simulating approval scenarios. The research contributes the first Machine Learning analysis of Nigeria's infrastructure approval drivers, offering actionable insights for optimizing project selection. The methodology demonstrates how machine learning can augment expert judgment in public investment decisions, particularly in resource constrained nations.

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1. INTRODUCTION

Infrastructure development is a major cornerstone of a nation's growth and a direct influence on the degree of national development. It directly influences productivity, job creation, urbanization, and the quality of life for citizens (Hoedemaekers, 2024). Inadequate infrastructure development remains a major barrier to attaining quality of life and inclusive economic growth in Nigeria. From clogged ports and badly maintained roads to insufficient social amenities and electricity supply. These infrastructure deficit is both a developmental, social, welfare, and economic concern (World Bank, 2024). In the past few years, different Nigerian government have invested into infrastructure project to fix these problem and reach national development goals like vision 2020 (National Planning Commission, 2009), the Economic Recovery and Growth Plan (ERGP) (Anam *et al.*, 2023), and the national integrated infrastructure master plan (NIIMP) (Federal Republic of Nigeria, 2020).

Despite these efforts, challenges such as project selection, poor implementations, funding constraints, and corruption remain major obstacles to Nigeria's Infrastructure development (Okpalaoka, 2021; Eja & Ramegowda, 2020). Some projects are initiated without a clear connection to long term strategic needs, and this is often driven by political considerations of regional balancing efforts (Gberevbie *et al.*, 2017). As a result, questions persist regarding the genuine incentives and factors influencing the prioritization and approval of infrastructure projects.

Understanding what truly drives project selection is critical not only for accountability but also for efficient allocation of limited public and donor resources. Traditional evaluation methods often rely on qualitative frameworks or cost benefit analytics that fail to account for multiple and important layers of social, environmental, and other strategic factors. This study proposes a novel, data driven approach that analyzes the key drivers that influence infrastructure project development in Nigeria. By leveraging expert opinion and machine learning techniques, this research provided a data driven framework for assessing and predicting the viability and approval of infrastructure projects.

By analyzing expert evaluation across different project drivers (economic, social, safety, environmental, political biases, and job creation), this study aims to highlight the most influential factor in project selection and construct a predictive model that approves or rejects a project based on driver inputs. In doing so, it provides evidence based insights that can inform infrastructure policies, promote transparency, and support long term planning.

2. LITERATURE REVIEW

The study of national infrastructure development has long occupied a central place in several disciplines such as environmental science, economics, engineering, urban planning, and public administration. Literature from the World Bank, International Monetary Fund, and United Nations Development Fund Programme consistently emphasizes the roles of infrastructure in stimulating economic growth, facilitating regional integration, and promoting equitable access to services. According to Calderon and Serven, Infrastructure stocks (measured by a synthetic index of telecom, power, and transport) have a positive and significant effect on GDP growth (Calderón & Servén, 2004).

The extant literature reveals several potential drivers of infrastructure development. These include economic benefits, social value, environmental Considerations, technology advancement, safety implications, and political influences.

In the Nigerian context, Emmanuel Eike and Nelson Christopher, in different articles, explored the macroeconomic implications of infrastructure investment, highlighting the strong correlation between government capital expenditures and sectoral development (Ochieka, 2025; Christopher *et al.*, 2025). However, these studies usually assess infrastructure through policies, concentrating on financial budg*et al*locations and implementation issues rather than the underlying frameworks for decision making. This limits our understanding of the typical selection and prioritization process for projects.

It is also widely acknowledged that infrastructure should be recognized for its social value, especially when it comes to delivering public services, fairness, and human development. Infrastructure like schools, hospitals, and housing has a direct impact on the quality of life of citizens and promises to help everyone grow (Manthey, 2024). Literature from the World Bank, Washington, D.C., noted that beneficial projects often receive public support and funding, particularly when they focus on vulnerable populations or underserved regions (Bigio, 1998).

Safety concerns often drive infrastructure improvements in sectors such as transportation and energy. For example, upgrades to road networks or electrical grids are frequently justified on the grounds of reducing accidents or preventing system failures. Literature from UN-Habitat documents how safety-related metrics should influence project prioritization (United Nations Human Settlements Programme, 2020)

Environmental considerations are increasingly central to infrastructure planning, particularly with the rapid rise of climate change policy and sustainability frameworks (Al-Humaiqani & Al-Ghamdi, 2022). Environmental impact assessment (EIA) laws in Nigeria and globally emphasize the importance of minimizing ecological harm (Ibrahim *et al.*, 2021). Ayo Olajuyigbe underscores how environmental risks and mitigation responsibilities now play a formal role in project design and approval (Okeukwu *et al.*, 2023).

Another pertinent indicator is technological advancement. Especially now that smart city projects, digital infrastructure, and automation are all rapidly advancing (Song *et al.*, 2023). The African Development Bank in 2023 noted that projects that present innovative ideas often get good support from donors and policymakers because of their long term efficiency and scalability (African Development Bank Group, 2023).

The final indicator- political bias or corruption - is perhaps the most contentious, y*et al*so most critical to investigate. Melvin D. Ayogu has investigated the political economy of infrastructure, noting that project selection often reflects political patronage, election cycles, and ethno-regional considerations (Ayogu, 2000). The World Bank mentioned that on the political side, mechanisms for rapid disbursement of project grants to poor municipalities have an obvious potential for partisan patronage and political advantage, particularly during election processes (World Bank, 1994). This view aligns with similar findings in other developing countries, where Infrastructure has been used as a political tool rather than a developmental instrument.

More recent literature has begun to embrace quantitative and data driven methods for infrastructure evaluation. Jelena M. Andruc and Jiayuan Wang did a fantastic job applying statistical methods, analytical hierarchical process (AHP), different fuzzy logic methods, Fuzzy-AHP method, and mixed methods to measure the sustainability performance of infrastructure projects under the Belt and Road Initiative (Andric & Wang, 2025). Likewise, machine learning applications in civil engineering have gained traction in areas such as structural health monitoring and resource optimization (Singh, 2024). This growing body of quantitative approaches demonstrates the field's evolution towards more rigorous, data centric evaluation frameworks.

There is a notable gap in applying machine learning to understand the decision making processes behind infrastructure development, especially in sub-Saharan Africa. While several frameworks exist for multi criteria decision analysis (MCDA), they often lack empirical data and are not validated using real-world project outcomes. This research contributed to filling that gap by combining expert knowledge with machine learning algorithms to drive data driven insight into the most Influential driver criteria behind infrastructure project approvals in Nigeria.

3. METHODOLOGY

3.1. Project selection and project sector distribution

30 major infrastructure projects commissioned in Nigeria within the last 5 years were selected, projects span key sectors including transport (road, bridges, rail) and energy (e.g., power plants, distribution infrastructure). The project selection prioritizes transport and energy sectors, mirroring the Buhari administration's documented infrastructure development, with the transportation sector ranking 50-55% and the energy sector 25% (Presidential Communication Team, 2023). A pie chart diagram showing sector classification of the selected project is displayed in Figure 1.

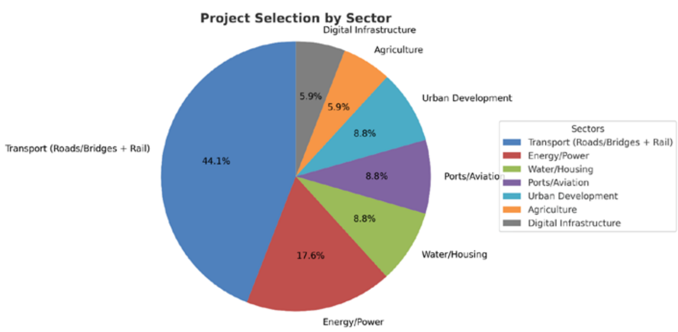

Figure 1. Project sector distribution

Project Driver Criteria Definition: Each project was assessed across 6 drivers of implementation, drivers were carefully selected based on a literature review, and they are defined as follows:

i. Economic Impact: This is the extent to which the project supports the nation's GDP growth, trade facilitation, and business productivity.

ii. Social Value: This has to do with how the project contributes to improving the quality of life and consideration for the underserved population.

iii. Safety Concerns: Whether the project addresses critical public safety needs, such as reducing transportation accidents and risk exposure.

iv. Environmental Consideration: The project alignment with sustainability goals and complies with environmental regulations.

v. Technological and Smart Advancement: Incorporation of innovation and state-of-the-art infrastructures.

vi. Political Bias/Corruption: There is perceived favoritism, political patronage, regional bias, or influence from election cycles, regardless of the project's developmental merit.

3.2. Expert rating and data collection

Data and ratings were collected by experts with relevant professional experience in project management, economics, public administration, engineering, and environmental management. 5 experts were paired with 10 projects respectively. Each expert had a minimum of seven years of professional experience and had been involved in infrastructure project evaluation, implementation, and monitoring. Each expert was asked to rate the extent to which each of the six drivers appeared to have influenced the implementation of each project on a scale of 1 to 5, where;

1 = not a driver at all
2 = minor influence
3 = moderate influence
4 = Strong influence
5 = Primary Driver

Multiple experts rated each project, and the average score per criterion was computed. The questionnaire was sent electronically, and some were filled out physically. Experts were given sufficient time to study projects they are not familiar with.

3.3. Data preprocessing and normalized weight analysis

i. Expert ratings were averaged per criterion for each project
ii. The data were standardized to the nearest positive integer to minimize rating scale bias
iii. Data was exported into CSV format for analysis
iv. Normalized average to determine key drivers of Infrastructure development based on data.

Each driver's mean rating was converted to a percentage contribution:

$$\text{Normalized weight}_i = \frac{\bar{x}_i}{\Sigma_{j=1}^{6} \bar{x}_j} \times 100\%$$

Where $\bar{x}_i$ is the mean rating for driver (e.g., economic impact), and the denominator sums all six drivers' averages. This converts each driver's influence to a percentage of total importance.

3.4. Machine learning analysis and predictive modeling

3.4.1. Model selection

A Random Forest Classifier was picked because of its ability to manage nonlinear and complex relationships and provide feature importance measures for interpretability. Before training, the synthetic minority oversampling technique (SMOTE) was used to reduce the class imbalance in the approval and rejection categories.

3.4.2. Data processing

i. Synthetic Minority Oversampling (SMOTE) balanced approval/rejection classes in the training set (70% of data)

ii. Test set (30%) preserved original distribution

All 30 projects in the dataset were successfully commissioned by the Nigerian government, to enable binary classification, a synthetic approval variable was generated. Projects with high economic impacts (≥ 4) and social value (≥ 3) were provisionally labeled as approved, while others were labelled as rejected. Approximately 25% of labels were randomly flipped to introduce controlled noise, and SMOTE was applied to balance the classes. This exploratory procedure allowed the random, forest model to simulate distinctions between higher and lower likelihood approvals, while acknowledging that actual unapproved projects were not available.

3.4.3. Random forest classifier

i. Parameters: 200 trees, max depth = 5, balanced class weights

ii. Target: Binary approval status (1 = Approved, 0 = Rejected)

iii. Validation: Classification report (precision/recall/F1) on test set

Feature importance from the model was extracted to identify which driver most influenced predictions. To determine the direction of influence, a partial dependence plot (PDP) analysis was performed, showing how each change in each driver score affected the predicted approval probability.

3.5. Interactive tool

The simulator tool was developed to allow for:

i. Adjust driver ratings (1-5 sliders) based on different scenarios.

ii. View approval probabilities.

iii. Identify top influencing factors

4. RESULTS AND DISCUSSION

This section presents the findings from expert evaluations and the exploratory machine learning analysis. Given the small dataset of 30 projects, the result should be interpreted as preliminary patterns rather than definitive conclusions. The discussion highlights the relative influence of different drivers, illustrates model behavior, and frames the observations as a hypothesis for future validation with a larger dataset.

4.1. Data Collection and Sample Characteristics

Fifteen infrastructure experts independently rated 30 Nigerian projects across six drivers (Economic Impact, Social Value, etc.) on a 1-5 scale. 5 experts rated 10 projects respectively. The averaged expert ratings (Table 1) reveal;

Table 1. Average expert ratings (1-5 Scale)

Driver	Mean Score	Rank
Economic Impact (1-5)	4.10	1
Social Value (1-5)	3.57	2
Safety Concerns (1-5)	3.16	3
Political Bias/Corruption (1-5)	2.70	4
Technological Advancement (1-5)	2.57	5
Environmental Consideration (1-5)	2.57	6

4.2. Determination of key drivers

Analysis of expert ratings revealed that economic impact (22.0%) was the most influential driver according to experts, followed by social value (19.1%) and safety concerns (17%). Technological advancement (14.5%), Environmental Consideration (13.8%), and Political Bias/Corruption (13.8%) were rated as less influential. Table 2 shows the combined driver weights in percentage. These weight represents each driver's proportional contribution to the total influence assigned by experts.

Table 2. Combined Driver Weights (%)

Driver	Expert Normalized Average (%)
Economic Impact (1-5)	22.0
Political Bias/Corruption (1-5)	13.8
Social Value (1-5)	19.1
Safety Concerns (1-5)	17.0
Environmental Consideration (1-5)	13.8
Technological Advancement (1-5)	14.5

4.3. Predictive modeling

A Random Forest classifier optimized with the SMOTE model is summarized in Table 3. On the test dataset, the model's overall accuracy was 67%, with an approval precision of 0.8, indicating that 80% of projects that were predicted as approved were approved. Equally with an 80% rejection recall, the model was able to identify 80% of projects that were rejected. Both classes, the F1-score was equal at 0.67, indicating that the model captures approvals and rejections equally well and without appreciable class imbalance.

Table 3. Random forest classifier performance

Metric	False (Reject)	True (Approve)	Overall
Precision	0.57	0.80	0.67
Recall	0.80	0.57	0.67
F1-Score	0.67	0.67	0.67
Support	5	7	12

4.3.1. Random forest driver importance

Table 4 Random forest driver importance. The Random Forest feature importance result (Table 4) indicates that economic impact (0235) and safety concerns (0.223) are the most influential predictors of project approval in the model. These are followed by environmental consideration (0.159) and political bias/ corruption (0.158), with Technological advancement (0.120) and social value (0.105) ranking lower.

While top ranking drivers in Table 4 partly align with the normalized expert weight in Table 4 (e.g., the emphasis on economic factors), some differences are notable. For example, environmental consideration ranks higher in the random forest model than in expert-assigned weights, suggesting that sustainability factors play a stronger role in approval outcomes than experts perceived in their assessment.

Table 4. Random forest driver importance

Driver	Importance Score	Rank
Economic Impact (1-5)	0.235	1
Safety Concerns (1-5)	0.223	2
Environmental Consideration (1-5)	0.159	3
Political Bias/Corruption (1-5)	0.158	4
Technological Advancement (1-5)	0.120	5
Social Value (1-5)	0.105	6

The Partial Dependence Plots in Figure 2 provide deeper insight into how each driver affects predicted approval probability when other variables are held constant:

i. Economic Impact (Figure 2, top left) shows a steep positive slope, with approval probability increasing from ~30% at a score of 2 to over 65% at a score of 5.

ii. Safety Concern (Figure 2, Top right) exhibits a similar upward trend, especially beyond a score of 3, indicating strong policy sensitivity to safety enhancing projects.

iii. Environmental Consideration (Figure 2, bottom left) has a clear positive influence, supporting the model's higher ranking of this driver compared to the expert's perception.

iv. Political Bias/Corruption (Figure 2, Bottom right) displays a generally negative relationship, where higher bias scores reduce approval probability from ~53% at low bias to ~43% at high bias. Despite its moderate ranking in Table 4, this supports the interpretation that political bias acts as a deterrent in the approval process.

v. Technological advancement exhibits a little positive trajectory, indicating incremental advantages from the integration of innovative solutions.

vi. Within this small dataset, social value appears relatively flat, suggesting a potentially weaker standalone influence. However, this result should be treated cautiously and tested with larger datasets.

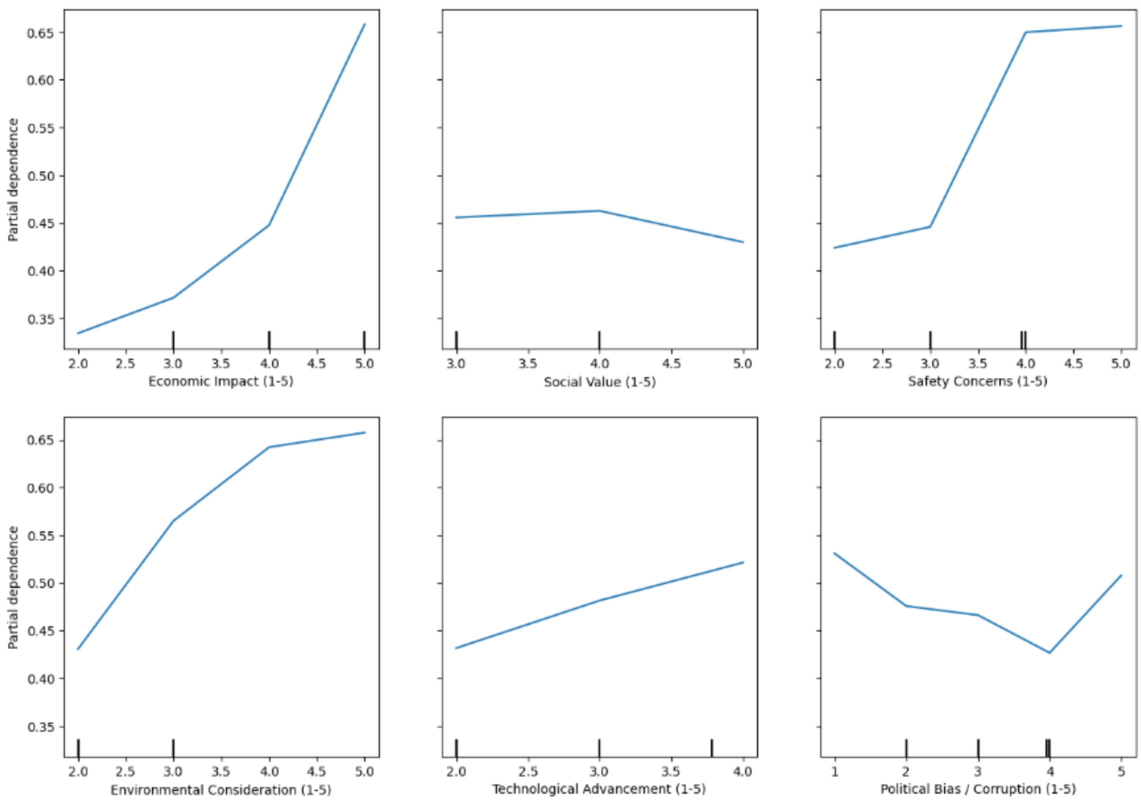

Figure 2. Partial dependence plot

4.4. Interactive prediction tool

To operationalize the random forest model for practical use, an interactive web based simulation tool was built Figure 2. The interface includes slider controls for each of the six project drivers on a 1-5 scale, enabling users to alter hypothetical project profiles and instantly receive a predicted approval probability. This functionality allows decision makers to investigate different scenarios and understand the trade-offs between drivers before submitting proposals for review. The tool was tested with multiple scenarios, and three example scenarios are illustrated in Table 5.

Table 5. Illustrative scenarios

Scenario	Inputs (Economic, Social value, Safety enhancement, Environment, Technology, and Political bias)	Predicted Approval	Interpretation
High Economic, Low Political	(5, 4, 4, 3, 3, 1)	71%	A strong economic case with minimal political interference results in a high likelihood of approval.
Moderate Economic, High Political	(3, 3, 3, 3, 3, 5)	45.8%	Even balanced technical scores are outweighed by high political bias.
Balanced Development	(4, 4, 4, 4, 4, 2)	81.7%	Broadly strong performance with low political bias sustains high approval chances.

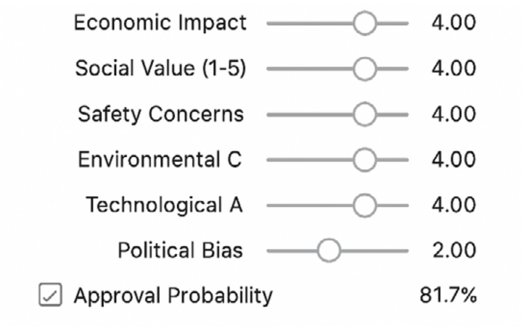

Figure 3. Interactive prediction tool

5. CONCLUSION

This research utilized expert evaluations and machine learning to identify the factors affecting infrastructure project approvals in Nigeria. The analysis indicated that, although economic impact and safety concern are the most influential elements, environmental considerations and political bias also significantly affect outcomes, with political prejudice constantly showing a negative influence on the chance of approval. The use of partial dependence plots elucidated the influence direction of each driver, reconciling the disparity between perceived and actual decision–making elements.

The development of an interactive prediction tool translated these findings into a practical resource, enabling policy makers and project proponents to test scenarios and optimize proposals for higher approval chances. By combining expert judgement with data-driven modelling, this research offers a transparent framework for more objective and evidence-based infrastructure decision-making in a resource-constrained nation like Nigeria.

The main limitation of this study is its small sample size of 30 projects, which restricts generalizability. While the random forest model achieved moderate accuracy, the results should be seen as exploratory. Future work should expand the dataset to include a larger and more diverse pool of both approved and unapproved projects to validate these preliminary insights and strengthen their policy relevance.

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