

Enhancing Stakeholder Coordination in Nigeria's Lithium Corridor: A Framework for Sustainable Strategic Mineral Development

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Abstract

Nigeria's emerging lithium industry presents significant opportunities for industrialization, job creation, local value addition, and economic diversification. However, achieving these benefits requires effective coordination among government agencies, mining companies, investors, research institutions, infrastructure providers, and host communities. This study develops a data-driven framework for evaluating stakeholder coordination within Nigeria's lithium corridor using survey data from 300 stakeholders. Six constructs—Governance Coordination, Infrastructure Readiness, Information Sharing, Investment Facilitation, Community Engagement, and Coordination Effectiveness—were validated using Cronbach's Alpha, the Kaiser–Meyer–Olkin (KMO) measure, Bartlett's Test of Sphericity, and Exploratory Factor Analysis (EFA). Five machine learning algorithms, namely Random Forest, XGBoost, LightGBM, CatBoost, and Decision Tree, were evaluated using Accuracy, Precision, Recall, F1-Score, and ROC-AUC, with SHapley Additive exPlanations (SHAP) applied for model interpretation. The results indicated excellent reliability (Cronbach's Alpha = 0.838–0.937), satisfactory sampling adequacy (KMO = 0.844), and significant Bartlett's Test ($p < 0.001$). Five factors explained 70.28% of total variance. CatBoost achieved the strongest performance, with 73.33% accuracy and 77.89% ROC-AUC. SHAP identified Governance Coordination, Information Sharing, Infrastructure Readiness, Investment Facilitation, and Community Engagement as the most influential predictors. The findings highlight stakeholder coordination as a critical mechanism for sustainable lithium value-chain development, investment, local beneficiation, and economic diversification.

Keywords: Lithium value chain; Stakeholder coordination; Job creation; Sustainable development; Artificial intelligence; (SHAP); Machine learning; Nigeria

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Introduction

The global transition toward low-carbon energy systems has substantially increased the demand for critical minerals, particularly lithium, which is an essential raw material for lithium-ion batteries used in electric vehicles, renewable energy storage systems, consumer electronics, and other clean energy technologies. As countries pursue carbon reduction and energy security objectives, lithium has become one of the world's most strategic mineral resources (Graham et al., 2021; Heredia et al., 2020). This growing demand presents resource-

rich developing countries with significant opportunities to diversify their economies, stimulate industrial development, and strengthen participation in the rapidly expanding global battery value chain.

Nigeria possesses substantial lithium deposits distributed across several states, positioning the country as one of Africa's emerging suppliers of critical minerals. According to Eniowo et al. (2026), these resources provide an important opportunity to reduce dependence on crude oil exports through mineral-based industrial development. Similarly, Zwanbin (2025) reported that the increasing global demand for battery minerals has enhanced the strategic importance of Nigeria's lithium corridor within international critical mineral supply chains. Furthermore, growing foreign investment, particularly from China and other international partners, has strengthened Nigeria's prospects of participating in global battery manufacturing and electric vehicle industries (Chun & Umar, 2026). Nevertheless, realizing these opportunities requires moving beyond the export of raw lithium ore toward local value addition, mineral processing, battery manufacturing, technology transfer, and workforce development.

Despite these opportunities, Nigeria's lithium sector continues to face important structural challenges. Much of the current mining activity remains concentrated on the extraction and export of raw minerals with limited domestic processing. Consequently, the sector generates relatively low economic returns, creates limited employment opportunities, and contributes insufficiently to domestic industrial development. Host communities also continue to experience inadequate infrastructure, limited technological capacity, youth unemployment, and restricted participation in the benefits generated from lithium mining. Without policies that promote local beneficiation, industrial clusters, skills development, and domestic manufacturing, Nigeria risks repeating the historical pattern observed in many extractive industries where abundant natural resources have generated limited long-term national development.

While these challenges have attracted increasing attention from researchers and policymakers, existing studies have primarily examined individual aspects of Nigeria's lithium industry rather than the broader institutional mechanisms required for sustainable sectoral development. Previous studies have investigated mineral governance, environmental sustainability, artisanal mining, investment policies, and international trade. For example, Eniowo et al. (2026) emphasized strengthening governance mechanisms to maximize the developmental benefits of Nigeria's mineral resources, while Rasouli (2024) discussed the geopolitical significance of lithium within the global energy transition. Kushwaha and Chandwani (2025) highlighted the importance of critical minerals for renewable energy technologies, whereas Chiteka and Enweremadu (2025) examined Africa's growing role in global battery manufacturing value chains. Although these studies provide valuable insights, limited empirical attention has been devoted to understanding how coordinated stakeholder engagement can support local value addition, industrial growth, and effective governance within Nigeria's emerging lithium industry.

Addressing these challenges requires effective coordination among multiple stakeholders, including government agencies, mining companies, investors, research institutions, financial organizations, infrastructure providers, educational institutions, environmental regulators, and host communities. Effective stakeholder coordination can improve policy implementation, facilitate industrial investment, strengthen infrastructure development, encourage local content participation, enhance workforce capacity, reduce operational conflicts, and support the

establishment of downstream lithium processing and battery manufacturing industries. Conversely, weak coordination may discourage investment, delay industrial projects, and reduce the overall effectiveness of development initiatives across the lithium value chain.

Understanding these complex institutional interactions requires analytical approaches capable of modelling multiple interrelated governance, infrastructure, investment, and community factors simultaneously. Conventional statistical analyses provide valuable insights but are often limited in capturing complex nonlinear relationships among stakeholders. Consequently, recent advances in artificial intelligence and machine learning offer powerful tools for analysing multidimensional socioeconomic systems and supporting evidence-based policymaking. In particular, machine learning algorithms can identify hidden patterns, model nonlinear relationships, and improve predictive decision-making. Moreover, Explainable Artificial Intelligence (XAI), especially SHapley Additive exPlanations (SHAP), enhances model transparency by quantifying the contribution of individual variables to prediction outcomes. Despite these advantages, the application of explainable machine learning to stakeholder coordination in strategic mineral governance remains largely unexplored, particularly within emerging lithium-producing economies such as Nigeria.

Against this background, this study develops a data-driven framework for evaluating stakeholder coordination within Nigeria's lithium corridor using explainable machine learning. Specifically, the study investigates how Governance Coordination (GC), Infrastructure Readiness (IR), Information Sharing (IS), Investment Facilitation (IF), and Community Engagement (CE) influence Coordination Effectiveness (COE). To achieve this objective, Exploratory Factor Analysis (EFA) is employed to validate the measurement constructs, while Random Forest, XGBoost, CatBoost, and Decision Tree models are developed to predict coordination effectiveness. SHAP is subsequently applied to explain the contribution of each stakeholder coordination factor to the predictive outcomes. By integrating statistical validation with explainable machine learning, this study provides empirical evidence on the institutional drivers of stakeholder coordination and offers an interpretable decision-support framework for policymakers, mining companies, investors, development partners, and host communities seeking to strengthen governance and promote sustainable development within Nigeria's lithium value chain.

Literature Review

Critical Minerals, Lithium Development, and Employment Generation

The increasing global demand for lithium has reinforced the strategic importance of critical minerals in accelerating the transition toward low-carbon and renewable energy systems. As an essential component of lithium-ion batteries used in electric vehicles, renewable energy storage systems, and advanced electronic technologies, lithium has become one of the world's most valuable strategic resources. This growing demand presents resource-rich countries with significant opportunities to stimulate industrialization, create sustainable employment, diversify national economies, and strengthen long-term economic resilience. Across Africa, governments are increasingly recognizing that the greatest economic benefits of lithium lie not merely in mineral extraction but in developing complete value chains that include mineral processing, battery manufacturing, component production, recycling industries, research and development, and skilled workforce development.

Several studies have emphasized that effective management of critical mineral resources can promote industrial growth, entrepreneurship, technology transfer, infrastructure expansion, and large-scale job creation (Kushwaha & Chandwani, 2025; Ndubuisi et al.). In Nigeria, substantial lithium deposits have attracted considerable domestic and international interest, creating opportunities to establish downstream industries capable of generating thousands of direct and indirect jobs while reducing dependence on crude oil revenues (Zwanbin, 2025; Chun & Umar, 2026). However, these opportunities can only be fully realized if Nigeria moves beyond exporting raw lithium ore toward local beneficiation, domestic manufacturing, and value addition that retain greater economic benefits within the country. Consequently, sustainable job creation has become one of the most important objectives of Nigeria's emerging lithium industry.

Stakeholder Coordination, Resource Governance, and Inclusive Development

The literature on Nigeria's mining and extractive sectors consistently highlights governance quality and stakeholder coordination as fundamental determinants of whether natural resources generate broad-based socioeconomic development. Eniowo et al. (2026) observed that institutional weaknesses, informal mining activities, inadequate regulatory enforcement, and revenue leakages continue to constrain the mining sector's contribution to national development. Similar concerns have been raised regarding environmental management, infrastructure provision, host-community participation, and investment coordination.

Ahmadnia et al. (2022) and Ranieri (2020) argue that effective governance structures improve regulatory compliance, reduce conflicts, enhance environmental sustainability, and promote equitable distribution of mining benefits. Beyond these governance outcomes, coordinated stakeholder engagement enables governments, investors, educational institutions, financial organizations, mining companies, and host communities to collaborate in developing industrial clusters, vocational training programmes, local supply chains, and employment opportunities. Strong coordination therefore plays a critical role in ensuring that lithium development contributes not only to mineral exports but also to sustainable livelihoods, poverty reduction, youth employment, and inclusive economic development.

Global Value Chains, Local Value Addition, and Industrialization

Recent scholarship has examined how global production networks, geopolitical competition, and foreign direct investment influence the development of Africa's critical mineral industries. Chun and Umar (2026) demonstrate that increasing Chinese investment has accelerated Nigeria's integration into global lithium supply chains, while Zwanbin (2025) highlights Nigeria's growing strategic importance within international battery mineral markets. Other researchers have emphasized that successful mineral-producing countries derive substantially greater economic benefits by developing domestic processing industries rather than exporting unprocessed raw materials (Mendez Parra et al., 2025; Usman et al., 2024; Rotimi-Ojo, 2025).

Developing local lithium processing plants, battery manufacturing facilities, component assembly industries, recycling centres, and supporting manufacturing ecosystems creates significantly higher employment opportunities than reliance on raw mineral exports alone. Such downstream industries stimulate entrepreneurship, strengthen small and medium-sized enterprises, encourage innovation, facilitate technology transfer, and increase demand for skilled labour across engineering, manufacturing, logistics, research, and technical services. Consequently, effective stakeholder collaboration is essential for attracting investment,

improving infrastructure, supporting industrial upgrading, and ensuring that Nigeria's lithium resources become a catalyst for large-scale job creation and sustainable industrial development.

Machine Learning for Policy and Strategic Decision Support

The increasing complexity of resource governance, industrial planning, and stakeholder interactions has stimulated growing interest in machine learning as a decision-support tool for public policy. Machine learning algorithms have demonstrated strong capabilities in identifying complex relationships, predicting outcomes, and supporting evidence-based decision-making across economic, environmental, and organizational domains. In governance research, algorithms such as Random Forest, Extreme Gradient Boosting (XGBoost), CatBoost, and Decision Tree have been successfully applied to evaluate multidimensional institutional and socioeconomic systems.

Furthermore, Explainable Artificial Intelligence (XAI), particularly SHapley Additive exPlanations (SHAP), improves model transparency by identifying the relative contribution of individual variables to predictive outcomes. Within the context of Nigeria's lithium industry, machine learning can assist policymakers in identifying the institutional, infrastructural, investment, and community-related factors that most strongly influence coordination effectiveness and ultimately affect industrial development, employment generation, and sustainable economic growth. Despite these advantages, the application of explainable machine learning to strategic mineral governance remains relatively limited, particularly in emerging lithium-producing economies.

Research Gap and Conceptual Foundation

Although existing studies have substantially improved understanding of critical mineral governance, environmental sustainability, investment policies, industrial development, and global value-chain integration, relatively little attention has been devoted to examining how stakeholder coordination can transform Nigeria's lithium resources into a sustainable source of employment, industrialization, and inclusive economic development. Most previous studies have concentrated on policy discussions, governance reforms, geopolitical considerations, or investment opportunities, while providing limited empirical evidence on the institutional factors that enable lithium development to generate widespread socioeconomic benefits.

Furthermore, previous research has rarely employed quantitative approaches capable of simultaneously evaluating governance coordination, infrastructure readiness, information sharing, investment facilitation, and community engagement as integrated drivers of industrial growth and job creation. The application of advanced machine learning and explainable artificial intelligence to support evidence-based policymaking in Nigeria's lithium sector also remains largely unexplored.

To address these gaps, this study develops a comprehensive data-driven framework for evaluating stakeholder coordination within Nigeria's lithium corridor as a pathway for promoting sustainable industrial development and employment generation. The framework integrates survey-based data collection with Exploratory Factor Analysis (EFA) to validate the measurement constructs, while supervised machine learning algorithms, including Random Forest, XGBoost, CatBoost, and Decision Tree, are employed to predict coordination effectiveness. SHapley Additive exPlanations (SHAP) are incorporated to identify the stakeholder coordination factors that contribute most significantly to effective governance and policy implementation.

The conceptual framework is grounded in organizational coordination theory and resource governance theory, which argue that effective governance, adequate infrastructure, efficient information sharing, investment support, and active community participation collectively strengthen institutional performance and facilitate sustainable development. Within Nigeria's lithium corridor, these factors are expected to promote local value addition, attract responsible investment, strengthen domestic manufacturing, enhance workforce development, encourage entrepreneurship, generate quality employment opportunities, and support long-term economic diversification. The findings therefore provide evidence-based guidance for policymakers, investors, mining companies, and development partners seeking to transform Nigeria's lithium resources into a strategic driver of industrialization, job creation, and sustainable national development.

Methods

Research Design

This study adopts a quantitative cross-sectional survey design to investigate the factors influencing stakeholder coordination within Nigeria's lithium corridor. A survey-based approach was chosen because it enables the systematic collection of standardised data from a broad spectrum of stakeholders involved in strategic mineral development, while simultaneously allowing for rigorous statistical analysis and predictive modelling. The research integrates classical statistical techniques with modern machine learning algorithms to identify the principal determinants of effective stakeholder coordination, thereby offering a data-driven framework for policy and managerial decision-making.

Population, Sampling Technique and Data Collection

The target population comprises key stakeholders actively participating in Nigeria's lithium value chain. These include government officials, mining companies, investors, policymakers, geologists, environmental practitioners, consultants, academics, and representatives of local communities. A combination of purposive and snowball sampling techniques was employed to reach knowledgeable respondents who possess direct experience with lithium governance, mining operations, investment planning, and policy implementation. The final sample consisted of 300 respondents, which provides sufficient statistical power for both classical factor analysis and machine learning modelling. Data were collected using a structured questionnaire administered electronically via Google Forms. The survey instrument was developed following an extensive review of the literature on resource governance, stakeholder coordination, industrial policy, and strategic mineral development. Before full deployment, the questionnaire was pre-tested with a small group of experts from academia, mining policy institutions, and industry to ensure content validity, clarity, and relevance. The final version was then distributed over a four-week period, with reminders sent at weekly intervals to maximise the response rate.

Survey Dataset Description

The final dataset comprises 300 observations and contains demographic variables together with 24 questionnaire items that measure six latent constructs associated with stakeholder coordination. Demographic variables: (1) Stakeholder sector (Government, Mining Company, Investor, Consultant, Academia, Community Organisation); (2) Years of professional experience (<5, 5–10, 11–15, >15). Latent constructs each measured by four items on a five-point Likert scale (1 = *Strongly Disagree* ... 5 = *Strongly Agree*): (1) Governance

Coordination (GC1–GC4); (2) Infrastructure Readiness (IR1–IR4); (3) Information Sharing (IS1–IS4); (4) Investment Facilitation (IF1–IF4); (5) Community Engagement (CE1–CE4); (6) Coordination Effectiveness (COE1–COE4)

For each construct, a composite score was computed as the arithmetic mean of its constituent items. For example, the composite Governance Coordination score is given by:

$$GC = \frac{GC_1 + GC_2 + GC_3 + GC_4}{4} \quad (1)$$

Similarly:

$$IR = \frac{IR_1 + IR_2 + IR_3 + IR_4}{4} \quad (2)$$

$$IS = \frac{IS_1 + IS_2 + IS_3 + IS_4}{4} \quad (3)$$

$$IF = \frac{IF_1 + IF_2 + IF_3 + IF_4}{4} \quad (4)$$

$$CE = \frac{CE_1 + CE_2 + CE_3 + CE_4}{4} \quad (5)$$

$$COE = \frac{COE_1 + COE_2 + COE_3 + COE_4}{4} \quad (6)$$

These composite scores serve as the predictor variables (GC, IR, IS, IF, CE) and the target variable (COE) for the machine learning models.

Reliability and Construct Validation

The internal consistency of the questionnaire was assessed using Cronbach's Alpha (α). A coefficient of 0.70 or higher was considered acceptable for demonstrating reliability.

Cronbach's Alpha is defined as:

$$\alpha = \frac{k}{k-1} \left(1 - \frac{\sum_{i=1}^k \sigma_i^2}{\sigma_T^2} \right) \quad (7)$$

where:

k = number of items in the construct,

σ_i^2 = variance of item i ,

σ_T^2 = variance of the total score.

Construct validity was examined using Exploratory Factor Analysis (EFA). Before conducting EFA, the suitability of the data for factor analysis was checked using two diagnostic measures: (1) Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy – values greater than 0.70 indicate that the data are suitable for factor analysis; (2) Bartlett's Test of Sphericity – a statistically significant result ($p < 0.05$) indicates that the correlation matrix is not an identity matrix, justifying the application of factor analysis. Principal component analysis

with Varimax rotation was employed to extract factors. Factors were retained based on: Eigenvalue > 1.0, Factor loadings ≥ 0.50 .

Descriptive and Correlation Analysis

Descriptive statistics including frequencies, percentages, means, standard deviations, minima, and maxima were first computed for all items and composite scores to summarise the sample characteristics. Subsequently, Pearson correlation coefficients were calculated to examine the bivariate relationships among the five predictors (GC, IR, IS, IF, CE) and the target variable (COE). Correlation matrices and heatmaps were generated to visualise the strength and direction of these associations.

Machine Learning Model Development

Following construct validation, supervised machine learning models were developed to predict Coordination Effectiveness (COE) from the five coordination factors. The predictive relationship is expressed as:

$$COE = f(GC, IR, IS, IF, CE) \quad (8)$$

where $f(\cdot)$ denotes the prediction function learned by the algorithm.

Two ensemble learning algorithms were implemented: (1) Random Forest (RF) – an ensemble of decision trees that reduces overfitting by averaging predictions across many trees; (2) Extreme Gradient Boosting (XGBoost) a gradient-boosting framework that builds trees sequentially, correcting errors of previous trees, and includes regularisation to enhance generalisation. These algorithms were selected because of their proven ability to model complex non-linear interactions, handle high-dimensional data, and deliver high predictive accuracy while being robust to multicollinearity. Prior to model training, the dataset was randomly partitioned into a training set (80%) and a testing set (20%), using stratified sampling to preserve the distribution of the target variable. Categorical variables were one-hot encoded, and numerical predictors were standardised to ensure comparability across algorithms. Hyperparameter tuning was performed using Grid Search Cross-Validation (5-fold) to identify the optimal set of hyperparameters for each model.

Model Performance Evaluation

The predictive performance of each model was evaluated using five standard classification metrics, calculated from the confusion matrix (True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN)).

Accuracy – overall proportion of correct predictions:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

Precision – proportion of positive predictions that are actually correct:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (10)$$

Recall (Sensitivity) – proportion of actual positives correctly identified:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (11)$$

F1-Score – harmonic mean of precision and recall:

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (12)$$

ROC-AUC – area under the Receiver Operating Characteristic curve, which measures the model's ability to discriminate between classes:

$$\text{ROC-AUC} = \int_0^1 \text{TPR}(\text{FPR}) d(\text{FPR}) \quad (13)$$

In addition to these metrics, model interpretability was enhanced through confusion matrices, ROC curves, and Precision-Recall curves. To ensure generalisability, 10-fold cross-validation was performed, and the mean accuracy and standard deviation were reported.

Model Explainability Using SHAP

To improve the transparency and interpretability of the XGBoost model, SHapley Additive exPlanations (SHAP) were employed. SHAP is a unified framework based on cooperative game theory that assigns each predictor a Shapley value representing its marginal contribution to the prediction, averaged over all possible feature subsets.

The SHAP analysis included the following visualisations: (1) SHAP Plot – displays the distribution of Shapley values for each feature across all test instances, indicating both importance and direction of effect; (2) SHAP Beeswarm Plot – similar to the summary plot but arranges points to show density, offering a more detailed view of impact; (3) SHAP Waterfall Plot – explains the prediction for a single respondent by showing how the base value (average prediction) is adjusted by each feature to reach the final prediction. SHAP Dependence Plot – illustrates how the SHAP value of the most important feature varies with its actual value, revealing possible non-linear relationships

Results and Discussion

This section presents the findings obtained from the survey of 300 stakeholders involved in Nigeria's lithium value chain together with the results of the subsequent machine learning analyses. The analysis follows the methodological framework described in the previous section and is presented in a logical sequence. It begins with the demographic characteristics of the respondents, followed by the assessment of the measurement instrument through reliability and construct validation. After confirming the adequacy of the measurement model, the validated construct scores are used to develop and evaluate machine learning models for predicting Coordination Effectiveness (COE).

The reliability of the measurement instrument is first assessed using Cronbach's Alpha, while the suitability of the dataset for factor analysis is examined using the Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. Subsequently, Exploratory Factor Analysis (EFA) is conducted to validate the underlying measurement structure of the stakeholder coordination constructs, namely Governance Coordination (GC),

Infrastructure Readiness (IR), Information Sharing (IS), Investment Facilitation (IF), Community Engagement (CE), and Coordination Effectiveness (COE).

Following construct validation, the composite construct scores are employed as predictor variables in the machine learning models. Random Forest (RF), XGBoost, LightGBM, CatBoost, and Decision Tree classifiers are trained and evaluated using an 80:20 train-test split with Grid Search Cross-Validation for hyperparameter optimization. Model performance is compared using Accuracy, Precision, Recall, F1-Score, and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). Additional evaluation tools, including confusion matrices, ROC curves, Precision–Recall curves, and cross-validation results, are presented to provide a comprehensive assessment of the predictive performance of the developed models.

To improve the interpretability of the best-performing model, SHapley Additive exPlanations (SHAP) are applied to quantify the contribution of each stakeholder coordination factor to the prediction of Coordination Effectiveness. SHAP summary plots, beeswarm plots, waterfall plots, dependence plots, and feature importance rankings are subsequently used to explain both the global and local behaviour of the predictive model.

The results are presented sequentially as follows: respondents' demographic characteristics, reliability analysis, construct validation, correlation analysis, comparative machine learning performance, and SHAP-based model interpretation. Each subsection first presents the statistical results before providing a concise interpretation of their relevance to the study objectives.

Table 1. Demographic Characteristics of the Respondents (N = 300)

Characteristic	Category	Frequency (n)	Percentage (%)
Stakeholder Sector	Community	58	19.3
	Investor	56	18.7
	Consultant	55	18.3
	Academia	47	15.7
	Government	46	15.3
	Mining Company	38	12.7
Years of Experience	Less than 5 years	78	26.0
	5–10 years	74	24.7
	11–15 years	72	24.0
	More than 15 years	76	25.3

Table 1 summarizes the demographic characteristics of the 300 respondents who participated in the survey. Community representatives constituted the largest stakeholder group (19.3%), followed by investors (18.7%) and consultants (18.3%), while mining company representatives accounted for the smallest proportion (12.7%). The respondents also exhibited a balanced distribution of professional experience, with 26.0% having less than five years of experience, 24.7% having 5–10 years, 24.0% having 11–15 years, and 25.3% possessing more than 15 years of experience. Overall, the distribution of respondents across stakeholder categories and experience levels indicates that the survey included participants with diverse professional backgrounds relevant to Nigeria's lithium value chain. This broad representation provides an appropriate basis for the subsequent reliability assessment, construct validation, and machine learning analyses.

Table 2. Reliability Analysis and Sampling Adequacy

Construct/Test	Items	Cronbach's Alpha / Value	Interpretation
Governance Coordination (GC)	4	0.930	Excellent
Infrastructure Readiness (IR)	4	0.919	Excellent
Information Sharing (IS)	4	0.928	Excellent
Investment Facilitation (IF)	4	0.937	Excellent
Community Engagement (CE)	4	0.918	Excellent
Coordination Effectiveness (COE)	4	0.838	Good
KMO Measure	–	0.844	Meritorious sampling adequacy
Bartlett's Test	$\chi^2 = 5427.825$, df = 276	p < 0.001	Significant

Table 2 summarizes the reliability and sampling adequacy statistics for the measurement instrument. Cronbach's Alpha values ranged from 0.838 to 0.937, exceeding the recommended threshold of 0.70 and indicating good to excellent internal consistency across all constructs. Investment Facilitation (IF) recorded the highest reliability ($\alpha = 0.937$), whereas Coordination Effectiveness (COE) exhibited the lowest but still acceptable reliability ($\alpha = 0.838$).

The Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy was 0.844, indicating that the sample was suitable for factor analysis. In addition, Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 5427.825$, df = 276, $p < 0.001$), confirming that the variables were sufficiently correlated to justify factor extraction. Collectively, these results demonstrate that the measurement instrument possesses satisfactory reliability and that the dataset is appropriate for Exploratory Factor Analysis (EFA).

Having established the reliability and sampling adequacy of the data, the next stage of the analysis examines the underlying factor structure of the measurement instrument using Exploratory Factor Analysis.

Table 3. Exploratory Factor Analysis Results

Total Variance Explained

Factor	Eigenvalue	Variance Explained (%)
Factor 1	5.173	14.649
Factor 2	3.692	14.502
Factor 3	3.415	13.987
Factor 4	3.227	13.712
Factor 5	2.718	13.427
Total	–	70.277

Factor Loadings

Construct	Loading Range
Governance Coordination (GC1–GC4)	0.853–0.889
Infrastructure Readiness (IR1–IR4)	0.820–0.880
Information Sharing (IS1–IS4)	0.851–0.869
Investment Facilitation (IF1–IF4)	0.858–0.899
Community Engagement (CE1–CE4)	0.829–0.878

Table 3 show the results of the Exploratory Factor Analysis (EFA). Based on the Kaiser criterion, five factors with eigenvalues greater than one were retained. Collectively, these factors explained 70.28% of the total variance, indicating that the extracted factors accounted for a substantial proportion of the variability in the dataset.

The rotated factor loading matrix further shows that all questionnaire items loaded strongly on their respective constructs, with factor loadings ranging from 0.820 to 0.899. These loading values exceed the commonly accepted threshold of 0.50, demonstrating strong associations between the observed variables and their corresponding latent constructs. The results therefore provide evidence of satisfactory construct validity and confirm that the measurement instrument adequately represents the underlying dimensions of stakeholder coordination used in the subsequent machine learning analyses.

To further evaluate the appropriateness of the extracted factor structure, the distribution of eigenvalues is illustrated using the Scree Plot presented in Figure 1.

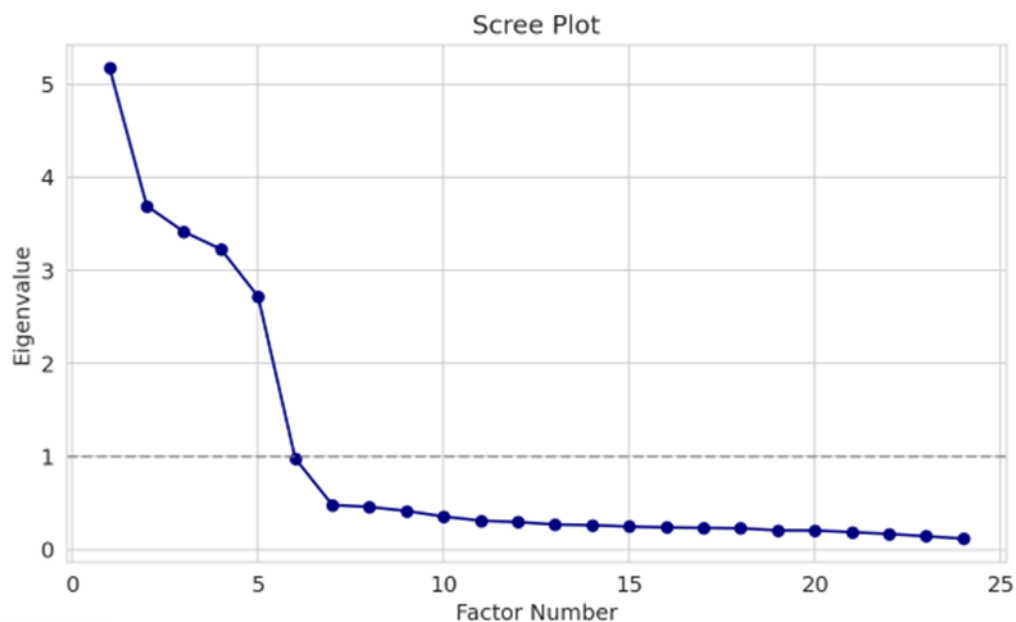


Figure 1. Scree Plot of the Exploratory Factor Analysis

Figure 1 illustrates the distribution of eigenvalues across the extracted factors obtained from the Exploratory Factor Analysis (EFA). The plot shows a sharp decline in eigenvalues from the first to the fifth factor, followed by a noticeable flattening of the curve. This distinct "elbow" after the fifth factor indicates that additional factors contribute relatively little to explaining the remaining variance. Consistent with the Kaiser criterion, five factors with eigenvalues greater than one were retained. The Scree Plot therefore provides graphical support for the five-factor solution identified in the EFA and confirms the suitability of the retained factor structure for the subsequent analyses.

Having established the underlying factor structure, the relationships among the validated stakeholder coordination constructs were subsequently examined using Pearson correlation analysis, as presented in Figure 2.

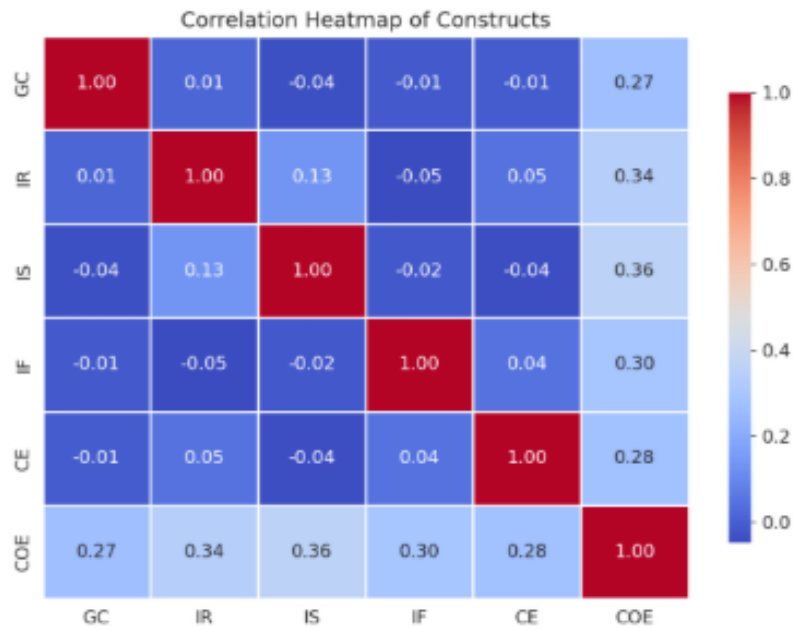


Figure 2. Correlation Heatmap of the Stakeholder Coordination Constructs

Figure 2 illustrates the Pearson correlation matrix among the six stakeholder coordination constructs: Governance Coordination (GC), Infrastructure Readiness (IR), Information Sharing (IS), Investment Facilitation (IF), Community Engagement (CE), and Coordination Effectiveness (COE). The heatmap indicates relatively low intercorrelations among the independent constructs, suggesting the absence of problematic multicollinearity. In contrast, Coordination Effectiveness (COE) exhibited positive correlations with all five stakeholder coordination constructs. The strongest relationships were observed for Information Sharing ($r = 0.36$) and Infrastructure Readiness ($r = 0.34$), followed by Investment Facilitation ($r = 0.30$), Community Engagement ($r = 0.28$), and Governance Coordination ($r = 0.27$).

These findings indicate that improvements in the stakeholder coordination constructs are associated with higher levels of Coordination Effectiveness. Furthermore, the relatively low correlations among the predictor variables suggest that each construct contributes distinct information, supporting their inclusion in the subsequent predictive modelling stage.

Having established the relationships among the validated constructs, the next stage of the analysis evaluates the predictive performance of the developed machine learning models for estimating Coordination Effectiveness.

Table 4. Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	0.6833	0.6190	0.5417	0.5778	0.7708
XGBoost	0.6833	0.6316	0.5000	0.5581	0.7662
LightGBM	0.7000	0.6875	0.4583	0.5500	0.7402
CatBoost	0.7333	0.6667	0.6667	0.6667	0.7789
Decision Tree	0.6000	0.5000	0.4167	0.4545	0.5683

Table 4 compares the predictive performance of the five machine learning models using Accuracy, Precision, Recall, F1-Score, and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). Among the evaluated models, CatBoost achieved the best

overall performance, recording the highest Accuracy (73.33%), Recall (66.67%), F1-Score (66.67%), and ROC-AUC (77.89%). These results indicate that CatBoost provided the strongest overall predictive performance and the greatest ability to distinguish between coordination effectiveness classes.

LightGBM achieved the second-highest Accuracy (70.00%) and the highest Precision (68.75%), indicating a comparatively lower rate of false-positive predictions. Random Forest and XGBoost demonstrated similar predictive performance, with both models achieving an Accuracy of 68.33%, although Random Forest produced slightly higher Recall than XGBoost. In contrast, the Decision Tree model recorded the lowest performance across all evaluation metrics, indicating comparatively weaker predictive capability for this dataset.

Based on the overall performance across the evaluation metrics, CatBoost was selected as the best-performing model for the subsequent explainability analysis. To further assess the classification performance of the developed models, Receiver Operating Characteristic (ROC) curves and Precision Recall curves are presented in the following subsection.

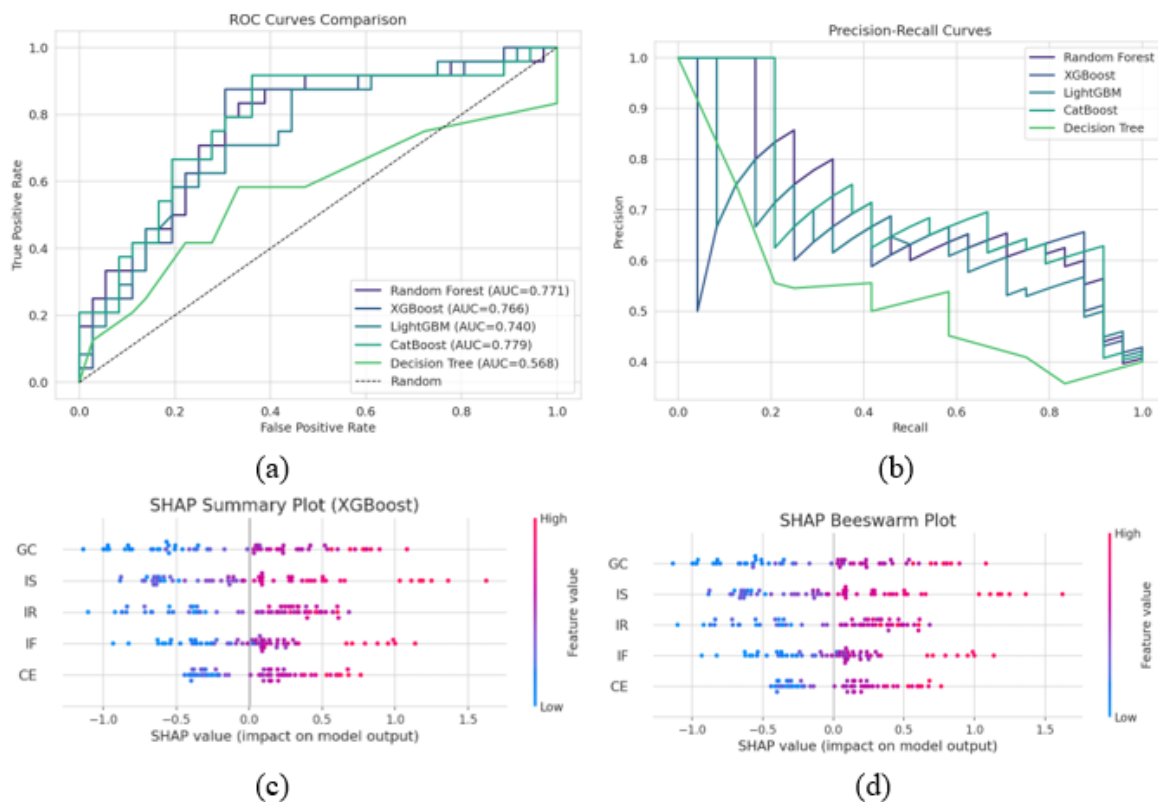


Figure 3. Performance Evaluation and SHAP-Based Interpretation of the Developed Models

ROC Curves Comparison

Figure 3(a) presents the Receiver Operating Characteristic (ROC) curves for the five machine learning models developed to predict Coordination Effectiveness. CatBoost achieved the highest ROC-AUC value (0.779), indicating the strongest discriminative ability among the evaluated models. Random Forest (0.771) and XGBoost (0.766) also demonstrated good classification performance, whereas the Decision Tree model recorded the lowest ROC-AUC (0.568), indicating comparatively weaker predictive capability. Overall, the ROC analysis

demonstrates that the ensemble learning models consistently outperformed the single Decision Tree classifier.

Precision Recall Curves

To further evaluate classification performance, Precision–Recall curves were examined, as shown in Figure 3(b). CatBoost maintained a more balanced trade-off between precision and recall across a wider range of thresholds, indicating greater stability in identifying Coordination Effectiveness. LightGBM achieved relatively high precision at lower recall levels, while Random Forest and XGBoost exhibited moderate but consistent performance. In comparison, the Decision Tree model showed the least stable precision recall relationship.

SHAP Summary Plot

After identifying CatBoost as the best-performing predictive model, SHAP analysis was employed to examine the relative importance of the stakeholder coordination constructs. Figure 3(c) presents the SHAP Summary Plot, which ranks the predictor variables according to their overall contribution to the model predictions. Governance Coordination (GC) emerged as the most influential predictor, followed by Information Sharing (IS), Infrastructure Readiness (IR), Investment Facilitation (IF), and Community Engagement (CE). Positive SHAP values indicate that higher values of these variables increase the likelihood of predicting higher Coordination Effectiveness.

SHAP Beeswarm Plot

Figure 3(d) presents the SHAP Beeswarm Plot, providing a detailed visualization of the distribution of SHAP values across individual observations. Higher values of Governance Coordination and Information Sharing were generally associated with positive contributions to the predicted Coordination Effectiveness, whereas lower values contributed negatively to the model output. The wider distribution of SHAP values for Governance Coordination indicates greater variability in its influence across the dataset, reinforcing its importance within the predictive model. Collectively, the results presented in Figure 3 demonstrate that CatBoost achieved the strongest predictive performance among the evaluated machine learning models, while the SHAP analysis identified Governance Coordination as the most influential predictor of Coordination Effectiveness. These findings provide the basis for the more detailed discussion of the practical and policy implications presented in the Discussion section.

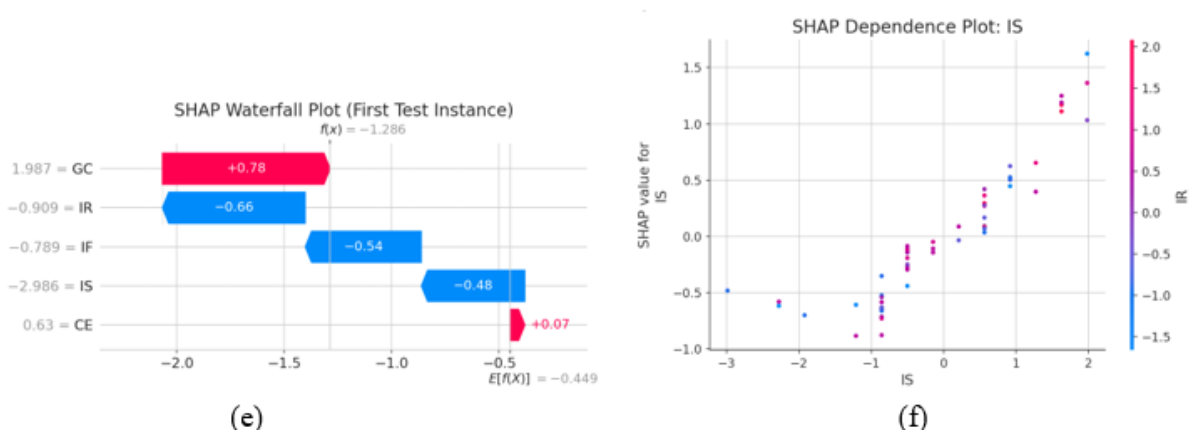


Figure 4. Local and Feature-Level Interpretation of the XGBoost Model Using SHAP

SHAP Waterfall Plot

To further explain the contribution of individual stakeholder coordination factors to a single prediction, a SHAP Waterfall Plot was generated for a representative test instance, as shown in Figure 4(e).

Figure 4(e) illustrates how each stakeholder coordination construct contributes to the final prediction of Coordination Effectiveness. The prediction begins with the model's baseline expectation and is subsequently adjusted by the contribution of each predictor. Governance Coordination (GC) made the largest positive contribution (+0.78), indicating that higher governance performance substantially increased the predicted Coordination Effectiveness for the selected observation. In contrast, Infrastructure Readiness (IR), Investment Facilitation (IF), and Information Sharing (IS) contributed negatively to the prediction, with SHAP values of -0.66 , -0.54 , and -0.48 , respectively, indicating that lower values of these variables reduced the predicted outcome. Community Engagement (CE) made a relatively small positive contribution (+0.07), suggesting a modest influence on the final prediction. Overall, the Waterfall Plot demonstrates how the combined contributions of the stakeholder coordination constructs determine the model prediction for an individual observation.

SHAP Dependence Plot

To further examine the relationship between individual predictor values and their influence on the model output, SHAP Dependence analysis was performed. The results are presented in Figure 4(f). Figure 4(f) presents the SHAP Dependence Plot for Information Sharing (IS). The plot shows a positive relationship between Information Sharing and its corresponding SHAP values, indicating that higher Information Sharing scores are associated with higher predicted Coordination Effectiveness. Conversely, lower Information Sharing scores produced negative SHAP values, reducing the predicted outcome. The colour gradient further indicates interactions with Infrastructure Readiness (IR), suggesting that the influence of Information Sharing becomes stronger under more favourable infrastructure conditions.

Collectively, the SHAP Waterfall and Dependence plots provide complementary local and feature-level explanations of the predictive model. While the Waterfall Plot explains how individual stakeholder coordination factors contribute to a single prediction, the Dependence Plot illustrates how changes in Information Sharing influence the model output across multiple observations. These results further reinforce the importance of Governance Coordination and Information Sharing in predicting Coordination Effectiveness and provide additional insight into the behaviour of the best-performing machine learning model. The practical implications of these findings for stakeholder coordination and sustainable lithium value-chain development are discussed in the subsequent Discussion section.

Following the empirical and explainable machine learning analyses, Figure 5 synthesizes the principal findings into a conceptual pathway illustrating the relationships among the validated stakeholder coordination constructs and their expected contribution to lithium value-chain development.



Figure 5. Conceptual Framework Linking Stakeholder Coordination to Sustainable Lithium Value-Chain Development

Figure 5 shows that Governance Coordination, Infrastructure Readiness, Information Sharing, Investment Facilitation, and Community Engagement collectively strengthen Coordination Effectiveness. Improved coordination is associated with greater investor confidence, enhanced policy implementation, and increased support for downstream value-chain activities, including local beneficiation, mineral processing, and related industrial development. The framework provides a conceptual summary of the empirical relationships identified in this study and serves as a basis for the broader practical and policy implications discussed in the following section.

Conclusion

This study developed a data-driven and explainable machine learning framework to evaluate stakeholder coordination within Nigeria's lithium value chain. Using survey data collected from 300 stakeholders, the study integrated Exploratory Factor Analysis (EFA) with supervised machine learning models to identify the institutional factors influencing Coordination Effectiveness (COE). The reliability and validity analyses confirmed that the measurement instrument possessed satisfactory psychometric properties, as evidenced by high Cronbach's Alpha coefficients, an acceptable Kaiser–Meyer Olkin (KMO) statistic, a significant Bartlett's Test of Sphericity, and a well-defined factor structure obtained through EFA. Among the evaluated machine learning algorithms, CatBoost achieved the best overall predictive performance, outperforming Random Forest, XGBoost, LightGBM, and Decision Tree across

the selected evaluation metrics. SHAP-based explainability further identified Governance Coordination, Information Sharing, Infrastructure Readiness, Investment Facilitation, and Community Engagement as the most influential predictors of Coordination Effectiveness. These findings address the identified research gap by providing a quantitative, interpretable, and evidence-based framework for assessing stakeholder coordination within Nigeria's strategic lithium sector. The study contributes to the existing literature by integrating statistical validation with explainable machine learning to evaluate stakeholder coordination in a strategic mineral governance context. Unlike previous studies that have primarily relied on descriptive or qualitative approaches, the proposed framework provides an interpretable decision-support tool capable of identifying the relative importance of stakeholder coordination factors while maintaining model transparency and predictive accuracy.

The findings also suggest that strengthening governance coordination, improving information sharing, enhancing infrastructure readiness, facilitating investment, and promoting community engagement may improve coordination effectiveness across Nigeria's lithium value chain. These insights provide an empirical foundation for policymakers, investors, industry stakeholders, and development partners to prioritize institutional and operational interventions that support responsible lithium resource governance and downstream value-chain development. Despite these contributions, this study has several limitations. The analysis was based on cross-sectional survey data collected from stakeholders within Nigeria's lithium corridor and therefore reflects stakeholder perceptions at a single point in time. Future research could employ longitudinal datasets, incorporate additional socioeconomic and environmental indicators, compare stakeholder coordination across multiple mineral-producing countries, and investigate advanced explainable artificial intelligence and hybrid machine learning techniques to further improve predictive performance and decision support for critical mineral governance.

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