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Evaluation of Stakeholder Perceptions and Applicability of Artificial Intelligence Integration into Environmental Impact Assessment Processes in Nigeria

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ABSTRACT: The integration of Artificial Intelligence (AI) into Environmental Impact Assessment (EIA) processes largely depends on stakeholder perceptions and the practical applicability. Hence, the objective of this paper was to evaluate the stakeholder perceptions and applicability of AI integration into EIA process in Nigeria using 307 semi-structured questionnaires to obtain data from government officials, environmental practitioners, academic researchers, NGO representatives, and community activists. Results revealed a significant gender imbalance, with 62% male and 38% female respondents. The majority of participants were within the 35-44 age group, with a notable under-representation of younger and older age groups. A high familiarity with AI was observed, with 93.2% of respondents reporting awareness. Confidence in the EIA process was generally positive, with 61.9% expressing trust in its decisions. However, concerns about stakeholder engagement and AI's role in enhancing EIA processes were highlighted. The findings suggest a strong potential for AI to improve EIA processes in Nigeria, particularly in automated monitoring and data collection. However, challenges in stakeholder engagement and the need for more inclusive demographic representation were noted. The integration of AI in Nigeria's EIA process shows promise but requires careful consideration of stakeholder concerns and demographic inclusivity. This study provides unique insights into the perceptions of diverse stakeholders regarding the integration of AI into Nigeria's EIA process, highlighting both opportunities and challenges.

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Evaluating environmental and social impacts is a critical stage in the EIA process, crucial for informed decision-making that supports sustainable development (Kaur, 2012). The effectiveness of EIA relies on providing decision-makers with accurate, relevant information to guide their choices, as emphasized by Nwoko (2013), and Liu *et al*. (2021). Key components of the EIA process include scoping, data collection, impact assessment, and the development of mitigation strategies (Rao *et al*., 2017). Successful EIA implementation necessitates the active involvement of diverse stakeholders, including professionals, government entities, and local communities (Ogunba, 2004). The quality of data, stakeholder engagement, and the effectiveness of mitigation measures are pivotal to the success of the EIA process. However, the EIA system in developing countries like Nigeria faces significant challenges,

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primarily in data acquisition, stakeholder participation, and resource availability (Ogunba, 2004). Obtaining reliable, up-to-date environmental data is difficult, which hinders accurate impact predictions and hazard identification. The credibility of the available data is also often questionable, further impeding effective environmental hazard forecasting and mitigation (Nwoko, 2013). Engaging stakeholders, especially local communities and indigenous populations, is another significant challenge. Many affected communities lack awareness of their rights and the potential impacts of projects, leading to opposition and poor management of concerns. Ensuring these stakeholders are actively involved in decision-making processes is crucial to address their concerns effectively. Resource constraints also hinder the effective execution of EIA in Nigeria. Government agencies responsible for monitoring EIA compliance often face financial and capacity limitations, resulting in inconsistent policy enforcement and inadequate studies (Nwoko, 2013). To enhance the EIA process, Nigeria should invest in environmental monitoring and data collection infrastructure, establish reliable baseline data, and conduct regular environmental assessments.

Training programs and public awareness campaigns are also essential to improve stakeholder engagement and the quality of EIAs (Rathi, 2023; Kaitei *et al*., 2022). Public participation is critical in the EIA process, but its absence in less developed nations poses significant challenges (Nadeem and Hameed, 2008). The under-engagement of local communities often leads to their perspectives being overlooked, resulting in conflicts that could delay or cancel projects (Nwoko, 2013). There is considerable potential to improve the EIA process through advanced data analysis, modeling methodologies, stakeholder engagement, and visualization technologies (Debrah et al., 2022).

AI technology can enhance decision-making by organizing and analyzing large datasets, leading to more accurate environmental impact predictions and models (Chapman, 2022). AI can also improve stakeholder participation by providing efficient communication channels. AI-powered tools like virtual assistants and chatbots create inclusive platforms for community members to voice their concerns and seek clarifications (Mleczko, 2021). Sentiment analysis tools further help gauge public support or resistance and pinpoint issues that need addressing (Fernandes *et al*., 2019; Koyamparambath *et al*., 2022). AI can monitor environmental data in real-time, enabling prompt responses to unforeseen changes (Zhang *et al*., 2021; Teng *et al*., 2021). By integrating AI, the EIA process can become more inclusive, transparent, and data-driven, enhancing environmental and societal impact assessments, community empowerment, and communication among stakeholders (Guisande *et al*., 2018; Zdravković and Panetto, 2022). However, it is essential to balance AI-driven efficiency with human-centered decision-making to ensure sustainable development while safeguarding ecosystems and communities.

In developing countries, AI presents a promising solution to the challenges of insufficient knowledge, limited resources, and inadequate public participation that often compromise EIA accuracy (Kaur *et al*., 2022). By improving project modeling, impact prediction, and stakeholder engagement, AI can enhance the quality of EIA reports (Wilson *et al*., 2017; Gerassis *et al*., 2021). AI's ability to analyze large datasets and create complex models provides accurate environmental impact predictions (Koyamparambath *et al*., 2022), equipping decision-makers with crucial information for informed decisions (Tukker, 2000; Toro *et al*., 2013). In Nigeria, AI can bridge information gaps and provide advanced analyses that traditional methods might miss, although ethical concerns such as biases in AI algorithms and data privacy must be carefully managed (Dwivedi *et al*., 2021; Huriye, 2023).

Hence, the objective of this paper was to evaluate the stakeholder perceptions and applicability of AI integration into EIA process in Nigeria

MATERIALS AND METHODS

Research Design and Data Collection: The research design employs a mixed-method approach to explore stakeholders' perspectives on integrating AI into Nigeria's EIA process, combining both quantitative and qualitative techniques (Osuizugbo and Nnodu, 2023). With a survey, featuring both closed-ended and open-ended questions, was distributed via Google Forms, hard copies, and various digital platforms, capturing comprehensive views on AI’s impact and challenges in EIA.

A total of 307 stakeholders from Nigeria's EIA process, including government officials, environmental practitioners, academic researchers, NGO representatives, and community activists.

Quantitative and Qualitative Data Analysis: Quantitative data from the survey were analyzed using statistical software to produce descriptive statistics such as frequencies, percentages, and central tendencies.

RESULTS AND DISCUSSION

Demographic and Occupational: The survey encompassed 307 respondents, with the demographic data revealing key insights into gender distribution, age groups, and occupations. The data indicates a notable gender imbalance, with 190 male participants and 117 female participants, representing approximately 62% of the sample as shown in Table 1. This imbalance does not necessarily reflect the gender distribution within the environmental sectors or imply a lower female response rate, but it does highlight a limitation due to the absence of precise personnel data in the study area.The majority of respondents are within the 35-44 age group, with 112 participants, followed by the 25-34 age group, which includes 68 participants. The under-representation of younger (18-24) and older (55 and above) age groups may affect the study's ability to capture diverse perspectives across different life stages. Future research should aim to achieve a more balanced age representation to gain a comprehensive understanding of attitudes towards AI in EIA. Occupationally, the survey includes a diverse range of participants, with the largest groups being academic/researchers (73) and NGO representatives (78). Environmental consultants, whose roles were merged with environmental practitioners (50), also provided valuable insights. This diverse representation enhances the study's ability to effectively evaluate the practical implications of AI integration in EIA processes.

Table 1: Demographic Profile of Survey Participants

Gender	Age Group	Occupation
Female	18 - 24	Environmental Consultant: 46
Male	25 - 34	Government Official: 45
	35 - 44	Environmental Practitioner: 3
	45 - 54	Academic/Researcher: 73
	55 and above	Non-governmental Organization Rep.: 78
	Other (Specify)	Community Member/Activist: 14
		Other (Specify): 48

Current EIA Practices in Nigeria

The efficacy of Nigeria's EIA process was evaluated through participant feedback, as shown in Figure 1. Ratings ranged from "Very Ineffective" to "Very Effective," providing a broad view of public perception. The survey indicated a positive outlook, with 114 participants (37.1%) rating the process as "Effective" and 71 (23.1%) as "Very Effective," totaling 60.3% of favorable responses. This suggests general satisfaction with the EIA process's ability to identify environmental risks and impacts. Several factors contribute to this positive perception. Recent enhancements in regulatory frameworks and enforcement, increased environmental awareness, and education may have improved EIA procedures (Nakwaya-Jacobus *et al*., 2021; McManamay *et al*., 2020). Effective stakeholder engagement, including government officials and community members, could also strengthen the process by incorporating diverse perspectives (Lawer, 2019). However, 27% of respondents rated the process as "Neutral," indicating mixed views on its effectiveness across different projects or regions. 39 participants (12.7%) expressed dissatisfaction, citing inconsistent application of guidelines, limited resources, and bureaucratic challenges as potential issues.

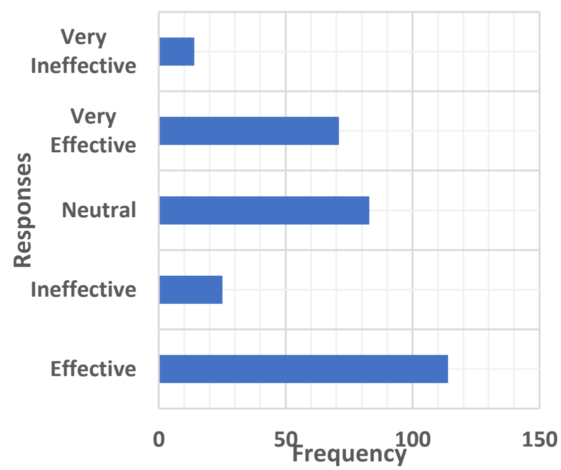

Fig. 1: Efficacy of the Current EIA Process in Nigeria

Participant responses regarding confidence in the accuracy of decisions based on Nigeria's current EIA process reveal varied levels of trust. 123 respondents (40.1%) rated their confidence as "Quite Confident," and 67 (21.8%) as "Very Confident," totaling 61.9% of positive responses. This indicates general trust in EIA-based decisions. Factors contributing to this confidence include effective stakeholder engagement, which improves the reliability of decisions by incorporating diverse perspectives, and increased transparency in the EIA process, which enhances trust in the methodologies used. However, 45 participants (14.7%) expressed "Somewhat Confident" feelings, suggesting moderate assurance with some reservations. This may be due to variability in EIA implementations or ongoing improvements that have not yet fully addressed all concerns. A notable 60 respondents (19.5%) were neutral, indicating mixed experiences or limited information about the EIA process. This neutrality may stem from inconsistent outcomes or lack of detailed knowledge about the process. A small group of 12 participants (3.9%) expressed low confidence, citing inefficiencies, past negative experiences, or concerns about corruption and bias as reasons.

AI Integration in Nigeria's EIA Process: Opportunities and Insights: Understanding participants' familiarity with AI is essential for assessing baseline knowledge and identifying potential biases in AI-related research. The survey reveals that 93.2% of participants (286 out of 307) are familiar with AI. This high level of familiarity is likely attributed to extensive media coverage (Rouxel, 2020), accessible online educational resources, and the widespread integration of AI across various industries. Conversely, 6.8% of participants (21 out of 307) reported not being familiar with AI. This lack of familiarity may be due to limited access to digital resources, educational backgrounds that do not emphasize technology, or personal disinterest in technological advancements. While the majority’s high familiarity provides a solid foundation for advanced discussions on AI, the minority’s lack of knowledge highlights the need for targeted educational initiatives to bridge this gap (Kumar *et al*., 2019).

The survey also assessed participants' understanding of AI applications in the EIA process, as illustrated in Figure 2. Respondents rated their understanding on a scale from "Very Low" to "Very High." Results indicate that 81 participants (26.4%) rated their understanding as "Very High," and another 81 (26.4%) as "High," totaling 52.8% with a strong grasp of AI’s potential in EIA frameworks. This high level of understanding may stem from professional experience in environmental science or AI, as well as the increasing integration of AI in environmental management (Benzidia *et al*., 2021). However, 111 respondents (36.2%) rated their understanding as "Moderate," suggesting general awareness but limited detailed knowledge or practical experience. 22 respondents (7.2%) rated their understanding as "Low," and 12 (3.9%) as "Very Low," indicating gaps in knowledge due to minimal exposure, educational limitations, or personal disinterest.

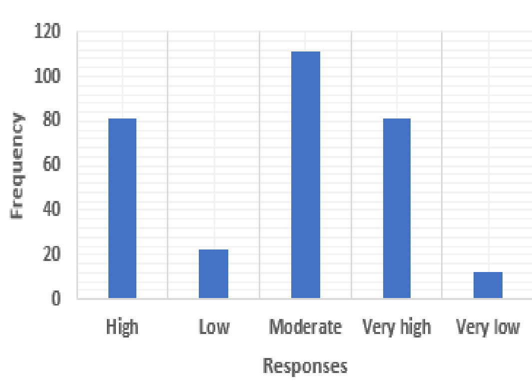

Fig. 2: Understanding of AI Application in the EIA Process

EIA process is essential for evaluating the environmental impacts of projects, but Nigeria faces challenges like inefficiencies in data collection, predictive inaccuracies, compliance monitoring issues, and complex stakeholder engagement (Osuizugbo and Nnodu, 2023). AI technologies can address these challenges effectively. AI can improve impact prediction and mitigation by using machine learning to analyze large datasets and uncover patterns missed by traditional methods. AI simulations model scenarios considering climate and socio-economic changes, aiding in the development of effective mitigation strategies (Mansfield *et al*., 2020). For data collection and analysis, AI automates processes with drones, remote sensors, and IoT devices, ensuring accurate, real-time data (Wang *et al*., 2019; Choi *et al*., 2021). Machine learning algorithms process this data to detect subtle environmental changes and integrate information from various sources (Janik *et al*., 2018; Scoville *et al*., 2021). AI also enhances monitoring and compliance through real-time data analysis and automated reporting, generating alerts for anomalies and improving overall compliance (Zhang *et al*., 2021). Effective stakeholder engagement is facilitated by AI through interactive platforms and NLP to analyze feedback from social media and surveys, promoting transparency and trust (Sachan *et al*., 2020).

AI in EIA - Benefits and Uses: The integration of AI into the EIA process holds significant potential to enhance various aspects of the procedure. Figure 3 summarize stakeholders' perspectives on the specific benefits that AI could bring to the EIA process in Nigeria. This discussion delves into the key themes identified from the responses and their implications for improving the EIA framework in Nigeria.

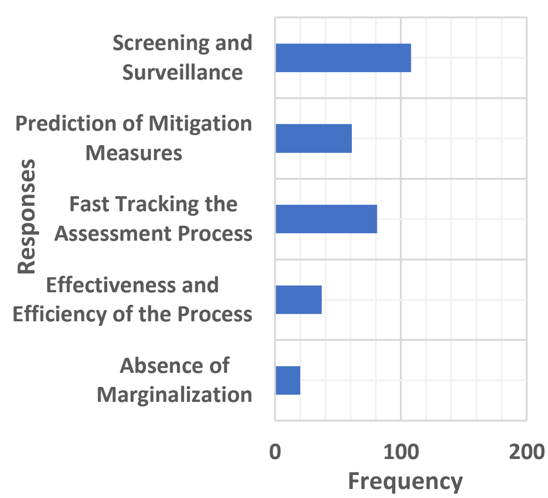

Fig. 3: Specific Benefits of AI in the EIA Process

The concept of "absence of marginalization" underscores AI's role in creating a more inclusive EIA process in Nigeria. Marginalization happens when stakeholders, particularly local communities and underrepresented groups, are excluded from decision-making. AI can counteract this by facilitating broader participation through digital platforms, enabling feedback collection from diverse stakeholders, including those in remote areas, via mobile technology and online surveys (Zou and Schiebinger, 2021). This approach promotes balanced assessments and equitable decision-making. AI can greatly enhance EIA efficiency. Traditional EIA methods involve labor-intensive data collection and analysis, which are prone to errors. AI can streamline these processes by automating data collection with sensors and remote technologies and analyzing large datasets for accurate impact predictions (Zhang *et al*., 2021). This not only speeds up assessments but also improves reliability. AI also has the potential to expedite the EIA process. Machine learning models can predict impacts using historical data, while NLP can automate regulatory reviews. AI simulations can model various scenarios to aid faster decision-making (Zumwald *et al*., 2021). AI improves mitigation measures by simulating and providing real-time feedback on different strategies (Satish *et al*., 2023). AI enhances screening and surveillance by automating criteria-based screening and monitoring conditions with smart sensors, drones, and satellite imagery, ensuring compliance and preventing violations. Integrating AI into Nigeria's EIA process could revolutionize environmental management and support sustainable development. The integration of AI into the EIA process offers a plethora of opportunities to enhance efficiency, accuracy, and inclusivity. Figure 4 provide an overview of stakeholder perspectives on the most promising uses of AI in the EIA process.

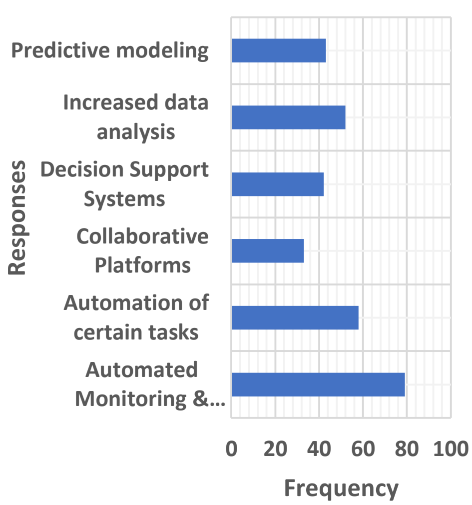

Fig. 4: Promising Uses of AI in the EIA Process

Automated monitoring and surveillance are frequently highlighted as promising applications of AI in the EIA process, with 79 respondents emphasizing their importance. This interest underscores the need for continuous, reliable environmental monitoring to ensure compliance with EIA recommendations and detect potential violations in real-time. AI technologies like drones, remote sensing, and smart sensors provide constant surveillance of environmental parameters, including air and water quality, land use, and biodiversity. AI-enabled drones capture high-resolution images to monitor deforestation and illegal activities, while smart sensors deliver real-time data on pollutants, triggering alerts when thresholds are exceeded (de Araujo *et al*., 2021). Automation of EIA tasks are another key benefit, noted by 58 respondents. Traditional tasks such as data collection and report generation are labor-intensive and error-prone. AI can enhance efficiency and accuracy by automating data collection and analysis, reducing manual input. NLP technologies can also streamline regulatory document reviews, ensuring compliance and thoroughness.

Collaborative platforms, mentioned by 33 respondents, show AI's potential to improve communication among EIA stakeholders. AI-driven platforms can centralize data, facilitate virtual meetings, and automate task scheduling, enhancing stakeholder engagement. AI-powered decision support systems, identified by 42 respondents, analyze complex datasets to aid decision-making, simulating scenarios and predicting outcomes for sustainable choices (Bressane *et al*., 2020). AI's ability to manage extensive data analysis was noted by 52 respondents. Technologies like machine learning and big data analytics can process large datasets efficiently, identifying patterns that inform better mitigation measures. Predictive modeling, highlighted by 43 respondents, can forecast environmental impacts under various scenarios, guiding better decision-making.

EIAs are vital for sustainable development, ensuring potential environmental risks are identified and mitigated. The integration of AI into the EIA process offers significant improvements in accuracy and reliability. A majority of 161 respondents agree, and 110 strongly agree that AI will enhance these aspects, while only one respondent strongly disagrees and 35 remain neutral, indicating broad support for AI integration. AI enhances accuracy by automating tasks prone to human error and analyzing large datasets from sources like satellite imagery and sensors, providing real-time predictions (Ditria *et al*., 2022). It also improves reliability by standardizing data collection and analysis. Despite general support, concerns about data privacy, costs, and technical expertise need addressing. Updating policies and engaging stakeholders can help Nigeria effectively leverage AI for more robust EIAs and better environmental management.

AI in Various Stages of the EIA Process: The integration of AI into the EIA process promises transformative improvements, with field data gathering emerging as a primary application. Traditional methods of data collection are labor-intensive and prone to errors. AI, through drones, remote sensors, and satellite imagery, can collect data over extensive and inaccessible areas, enhancing accuracy and timeliness while facilitating quicker decision-making. Another critical application of AI is in impact assessment and mitigation. AI's predictive modeling and machine learning capabilities enable detailed simulations of various scenarios and potential environmental impacts. This approach not only assesses the effects of proposed projects but also forecasts the outcomes of different mitigation strategies, aiding decision-makers in selecting the most effective measures. AI's ability to update models with new data allows for adaptive management, ensuring ongoing effectiveness of mitigation strategies (Murari *et al*., 2020). AI also plays a significant role in developing Environmental Management Plans (EMPs) by analyzing large datasets to identify effective management strategies and streamline monitoring and reporting, reducing administrative burdens (Choi *et al*., 2021). During screening and scoping, AI uses NLP to review project proposals and identify critical environmental concerns, ensuring comprehensive assessments (Gerassis *et al*., 2021). In environmental monitoring and compliance, AI automates processes with smart sensors and IoT devices, providing real-time data and enabling proactive management.

Challenges in Applying AI to the EIA Process: Stakeholder engagement is noted as the most challenging aspect of integrating AI into the EIA process, with 153 respondents highlighting this difficulty. This challenge arises from the complex human interactions involved in engaging diverse groups with varied interests and concerns. Effective engagement requires empathy and nuanced communication, areas where AI currently falls short. While AI can help organize and analyze feedback, it lacks the human touch needed to build trust, understand subtle cues, and foster meaningful dialogue. AI may struggle with socio-cultural dynamics and ethical concerns such as confidentiality and informed consent. Similarly, EMPs pose challenges for AI. While AI can analyze data and predict outcomes, creating EMPs requires deep contextual understanding and expert judgment, which AI lacks (Nishant *et al*., 2020). Customizing EMPs to specific project conditions often demands input from various disciplines. Field data gathering also presents difficulties. While AI technologies like drones and sensors aid data collection, they may face challenges in complex terrains or extreme conditions, where human intervention is often needed to ensure data accuracy (Dewitte *et al*., 2021).

AI in Enhancing Understanding of Complex Environmental Interactions: AI technologies hold substantial promise for transforming environmental assessments by identifying complex relationships and patterns within environmental data. This capability is vital for understanding cumulative impacts, feedback loops, and synergistic effects—factors that traditional methods often struggle to detect. Stakeholders in Nigeria's environmental assessments recognize this potential, with 210 out of 307 respondents agreeing that AI enhances the understanding of these complex interactions. Cumulative impacts, which result from the gradual accumulation of multiple environmental activities, can be challenging to assess due to their slow onset and multifaceted nature. AI can analyze large datasets from satellite imagery, sensor networks, and historical records to uncover patterns indicative of cumulative impacts, such as shifts in land use, water quality, and air pollution levels. Feedback loops, where initial environmental changes trigger further alterations that either amplify or mitigate the original effects, are crucial for predicting future conditions. AI, employing machine learning and neural networks, can model these complex ecosystem interactions and identify feedback mechanisms. AI can analyze data on deforestation and climate change to understand how these factors interact, aiding in the development of effective mitigation strategies. Despite the positive view from the majority, some respondent's express skepticism or neutrality. Concerns include the quality and availability of environmental data in Nigeria, which could lead to unreliable AI models if data collection infrastructure is inadequate. Addressing these concerns requires investment in data collection technologies and robust data management practices. The complexity and interpretability of AI models pose challenges; developing explainable AI systems that provide clear insights into their decision-making processes is essential for overcoming these issues (Karim *et al*., 2023). AI's ability to build predictive models using historical and real-time data significantly improves the forecasting of environmental impacts. By simulating various scenarios and accounting for multiple variables, AI can predict future conditions, such as the effects of climate change on water resources. Real-time monitoring, enhanced by AI, allows for continuous tracking of air and water quality, enabling early detection of anomalies and timely interventions (Sha *et al*., 2021).

Conclusion: The survey reveals key insights into the demographic and occupational traits of respondents, highlighting both strengths and limitations. A gender imbalance and under-representation of certain age groups suggest gaps in capturing a full range of perspectives, particularly from younger and older participants. Occupational diversity, however, enhances the study's ability to assess AI integration in EIA. Positive perceptions of Nigeria's EIA process indicate growing confidence, though mixed views show challenges like inconsistent application and resource limitations. High AI familiarity among respondents' signals potential for future innovations, though knowledge gaps suggest a need for targeted education. Addressing demographic imbalances, improving stakeholder confidence, and closing knowledge gaps are essential for maximizing AI's benefits in Nigeria's EIA process.

Declaration of Conflict of Interest: The authors declare that there are no conflicts of interest.

Data Availability Statement: The data supporting this study are available upon request from the first or corresponding author, as well as any of the co-authors.

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