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AI-driven Tools for Implementation of Smart Cities in Nigeria: An Agile Perspective

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Abstract: This study investigates the incorporation of artificial intelligence (AI)-driven technologies, in facilitating automation, intelligent decision-making, predictive analytics, and responsive urban management, as essentials to the change inherent in developing smart cities. This need for efficiency, sustainability, and improved quality of life has led to a radical change in contemporary urban planning as urban areas are gradually developing into smart cities. Through networked systems and real-time data analysis, smart cities use cutting-edge technologies to optimize governance, infrastructure, and services. Smart energy grids, waste optimization, adaptive traffic control, and customized citizen services are all made possible by these technologies. However, an agile and iterative approach to technology implementation is necessary due to the dynamic and complex nature of urban systems. This study examines Agile methodology as a strategic framework for the creation and application of AI-driven tools in smart city settings. Agile's fundamental principles, namely collaborative development, incremental delivery, and responsiveness to change, align well with the demands of adjusting to changing user needs, technological advancements, and sociopolitical factors. This study examines how Agile practices support stakeholder coordination, iterative prototyping, and quick adaptation in AI-based urban solutions through a mixed-methods research design that includes case studies from a few chosen smart city initiatives. The results show that the proposed Nigeria Agile Integration for Smart City Transformation (NAI-SMART) framework showed that Abuja, Enugu, and Ibadan are more technology-compliant at the time of this study than a few other cities used in this research. NAI-SMART was able to achieve this via AI-based technologies namely GRU time series model, Reinforcement learning, XGBoost, and Scikit-learn that were employed during NAI-SMART Urban Intelligence Engine (NAI-SMART UIE) model creation. This research therefore, contributes to both theory and practice by proposing a step-by-step framework for AI-powered smart city development using Agile principles. Ultimately, the study underscores the synergistic potential of AI and Agile in actualizing the vision of inclusive, data-driven, and adaptive smart cities in Nigeria.

Index Terms: Smart Cities, AI-Driven Tools, NAI-SMART, NAI-SMART UIE, Urban Digitization, Agile

1. Introduction

The 21st century's fast urbanization has presented city planners with previously unprecedented opportunities and challenges. Cities must adjust to mounting demands on housing, transportation, infrastructure, and the environment, as over 55% of the world's population lives in urban areas, a percentage that is predicted to increase to 68% by 2050 [1]. As a result, the idea of a "smart city" has surfaced as a crucial remedy that uses information and communication technology (ICT) to enhance urban living. In order to improve governance, maximize resource use, and improve the quality of life for citizens, smart cities incorporate digital technologies into their systems and services [2]. These technologies include cloud computing, IoT (Internet of Things), artificial intelligence, and data analytics. In addition to improving urban efficiency, smart cities seek to solve enduring problems like traffic, pollution, and social injustice. In order to make evidence-based decisions in real time, a smart city must be able to gather, evaluate, and act upon data from various sources, including energy consumption, traffic patterns, and public safety metrics. But moving toward smart urban environments calls for more than just implementing new technology; it also calls for reevaluating urban policy, governance, and the relationship between citizens and local government administrators.

Smart cities are made up of a number of interrelated systems that work together thanks to technology. These elements include using data-driven methods to support multimodal transport systems, improve public transportation, and lessen traffic; focusing on sustainability through effective waste management, pollution control, and the use of renewable energy [3]; utilizing digital services to improve public safety, healthcare, and education; stressing the development of human capital, digital literacy, and social inclusion; and promoting participatory governance through digital platforms that allow for citizen engagement, transparency, and accountability [4]. The urban experience is transformed by the dynamic interaction of these pillars. Real-time bus tracking is one example of a smart mobility initiative that can not only increase convenience but also lower carbon emissions and create a cleaner environment. From human and social dimensions, smart city development has inclinations to ethical, cultural, and governance influences. Reliance on intensive data collection may create multiple privacy bottlenecks. However, the use of sensors, cameras, transaction logs, mobile traces create room for generation of urban big data, enabling city systems to be managed in real time [5]. To avoid critical exclusions, smart city development has to consider accessibility for people with disabilities, multilingual interfaces for diverse populations, and culturally sensitive engagement practices [6]. The success of smart cities depends on governance structures that coordinate multiple public agencies, private vendors, civil society, and citizens. The effectiveness of the policies is bent on clear legal frameworks (such as data protection, and procurement rules), regulatory sandboxes for safe experimentation, performance and equity KPIs (Key Performance Indicators), and institutional capacity building to enable proper management and evaluation of complex AI systems [7].

Traditional urban planning, which frequently depended on static, long-term projections, has fundamentally changed with the incorporation of smart technologies. By integrating real-time data into decision-making, smart cities give planning procedures flexibility and responsiveness. Better emergency response systems, more focused environmental interventions, optimized traffic flows, and adaptive infrastructure development are all made possible by this. These days, urban planners monitor infrastructure requirements, visualize the effects of zoning decisions, and interact with the public through interactive platforms using digital tools like GIS (Geographic Information Systems) and urban simulation models [8]. Resilient cities, with urban settings that can foresee and bounce back from social, environmental, and economic upheavals, are made possible by these technologies. Furthermore, by taking into account the needs of all citizens, including the marginalized, smart city planning encourages inclusive urbanization. For instance, information from surveys and sensors can identify underprivileged areas, directing the fair allocation of funds and services.

Smart city initiatives have been implemented in a number of cities worldwide, with differing degrees of success. Barcelona, for example, is well known for using IoT to control its parking, traffic, and lighting systems. Additionally, it has open data platforms that encourage openness and participation from citizens using civic platforms, participatory budgeting, and public consultations to shape which technologies get deployed and how data are governed [9]. To increase productivity and quality of life, the Singaporean government created the "Smart Nation" initiative, which combines e-governance, intelligent transportation, and digital identity systems. For planning, research, and public involvement, its Virtual Singapore project offers a dynamic 3D city model. Using Vendor-led technology, Singaporean model optimized e-governance, intelligent transportation, and digital identity via better routing and energy scheduling. With an emphasis on e-governance services, walkable communities, and retrofitting urban infrastructure, India's "Smart Cities Mission" seeks to establish 100 smart cities. Leveraging the synergy of life sciences, sustainable energy, and ICT, Silesian and Lesser Poland Voivodship in Poland effectively manage smart cities using human-centric approach [10]. These initiatives represent a growing global trend toward tech-driven urban renewal, despite obstacles. Not every implementation, though, has been without its detractors. Data privacy, digital surveillance, and exclusionary outcomes have become concerns, particularly when technological advancements surpass legal protections [5]. Barcelona's participatory model proved slower and could not deliver rapid technical fixes for urgent operational problems. For cities with limited institutional capacity, Vendor-led technology poses high risks vendor lock-in, and raises serious privacy and governance concerns, leading to loss of public value and accountability [11]. Urban informatics which formed the major focus of India's "Smart Cities Mission" naturally assumes significant baseline technical capacity, data standardization, and sustained investment in platforms, of which these conditions are not obtainable in many cities [5]. The human-centric approach adopted in Poland require careful facilitation and capacity building, else, it may not open meaningful channels for citizen input. These issues highlight the necessity of community-centred planning methods and ethical frameworks in smart city development.

Smart cities are a game-changer for urban development in developing nations like Nigeria, where rapid urbanization and infrastructure problems necessitate creative solutions. Smarter management of public safety, waste, energy, transportation, and healthcare is becoming more and more necessary as a result of the growing population density in cities like Lagos, Abuja, Ibadan, Enugu, Kano and other prominent urban areas. Through data-driven insights, predictive analytics, and real-time responsiveness, the integration of AI-driven tools in Nigerian urban centres has enormous potential to improve service delivery. Through intelligent platforms, these tools can help cities monitor environmental pollution, manage traffic congestion more effectively, distribute power efficiently, and increase citizen engagement. Furthermore, implementing AI in urban governance can promote resilient and sustainable cities that meet international smart city standards by reducing costs and increasing transparency and proactive planning. In the Nigerian context, adopting AI-driven smart cities in Nigeria promises tangible benefits namely efficiency, better services, transparency. However, these can be constrained by socio-economic, infrastructural, and political/governance barriers. For instance, meagre incomes and precarious livelihoods whereby many households lack the ability to purchase Internet-enabled devices, pay for continuous broadband, or participate in digital services [12]. Despite Nigeria's rapid growth in online users, a substantial portion of the population remains offline. This is inimical to any smart city program because it cannot thrive among people who lack devices, reliable data, or the skills to use services [13]. As a complex social society, Nigeria faces the risk of poor representation of informal economic practices that characterized the nation in her quest for developing models that can implement smart cities. This is simply because AI systems trained on formal sector data do not fit into the design that classify large user groups [14]. Furthermore, the Nigerian society has evolved into a situation of no trust to the point that citizens are reluctant to share data or rely on automated decisions, leading to low participation in smart cities program [15,16]. Moreso, there is need for robust backup solutions regarding Nigeria's grid due to frequent outages and systemic collapses that mar electric supply in the country [17]. Besides, there would always be fear of weak coordination that characterizes the federated mandates and funding flows required to sustain the AI-based infrastructure project namely smart city [18].

In view of these, human-centric design must be given top priority in smart city development. Urban transformation should be viewed as facilitated by technology rather than being driven by it. In addition to innovation, strong institutional capacity, cross-sector cooperation, and citizen participation will be necessary for success [19]. Hence, this paper discusses the enabling characteristics of AI-driven tools that can offer the necessary human-centric services for the realization of smart cities particularly in developing nations like Nigeria. In other words, it investigates into how Agile methodology can be used to successfully implement AI technologies in order to satisfy Nigeria's demands for urban development. This helps to provide answers to three research questions: (1) What are the most pressing urban challenges in Nigerian cities that necessitate the adoption of AI-driven tools? (2) To what extent are Nigerian cities (e.g., Lagos, Abuja, Kano, Port Harcourt) technologically and infrastructurally prepared to integrate AI-driven solutions into smart city development? (3) What are the perceptions of policymakers, urban planners, and residents regarding the adoption of AI-driven technologies for smart city development? The objectives of this study include: (1) to assess the current state of urban challenges in a few Nigerian cities and determine their preparedness for smart city transformation; (2) to investigate how AI-driven tools can be used to address particular urban issues like waste, traffic, and security; (3) to investigate how Agile principles can be applied to the planning and execution of smart city projects; and (4) to create a workable framework for combining AI and Agile approaches that is suited to Nigeria's socioeconomic and infrastructure context. These objectives would specifically provide insights for policymakers, urban planners, residents, and technology developers on the best strategies on how to work towards smart and more inclusive urban future in Nigeria. This paper is divided into 6 sections. Sections 1 and 2 present introductory background of the study and a review of existing literatures in the research area respectively. Section 3 describes the methodology adopted in designing the NAI-SMART framework and its accessories, section 4 discusses the result from the NAI-SMART UIE model, section 5 presents some assertions deduced from the findings, and finally, section 6 makes a few recommendations that may guide future research towards building smart cities in Nigeria. The goal of this research is to provide useful information to technology developers, policymakers, and urban planners who are aiming to create a more intelligent and inclusive urban future in Nigeria.

2. Literature Review

Smart technologies are being used more and more in urban areas across the world to manage waste and energy, enhance public services, streamline transportation systems, and encourage citizen participation. Theoretically, an interconnected urban ecosystem with smooth data flow between systems would enable adaptive governance and real-time decision-making. However, in reality, a number of obstacles ranging from data management challenges, interoperability issues, governance gaps, infrastructure limitations, and digital inequality limit the development of smart cities [20]. Smart cities seek to improve urban sustainability, efficiency, and quality of life by combining sensor networks, data analytics, and information and communication technologies (ICT) [2]. However, despite the potential of this digital urban revolution, there are many technical, sociopolitical, economic, and ethical obstacles in the way of creating smart cities.

The fundamental digital infrastructure required to support smart technologies is lacking in many cities. According to [21], legacy systems frequently cannot be integrated with contemporary platforms, resulting in expensive and difficult procedures. Massive amounts of data are produced by smart cities. One of the main concerns is making sure that this data is gathered, saved, processed, and distributed in a safe and effective manner. Furthermore, because of proprietary technologies or a lack of standardization, interoperability across various platforms and systems is crucial but frequently absent [22]. The attack surface for cyber threats increases as urban systems become more digitally connected. Attacks on infrastructure, misuse of surveillance, and data breaches are all possible in smart cities. A delicate and constant concern is striking a balance between data utility and individual privacy [5]. If digital access is not distributed fairly, smart city initiatives may unintentionally exacerbate already-existing social inequalities. Because they lack representation in decision-making processes, connectivity, or skills, marginalized groups may be excluded from smart services [23]. Adaptive governance frameworks that can handle the rapidly evolving fields of technology, data ethics, and citizen rights are necessary for the successful deployment of smart cities. However, many cities lack well-thought-out plans or legal structures to deal with these demands [4].

However, the emergence of artificial intelligence (AI), which includes robotics, computer vision, natural language processing, and machine learning, has accelerated as a revolutionary force in urban management and planning. AI has the potential to improve almost every aspect of smart city life, including waste management, public safety, healthcare, energy, and transportation. For example, real-time traffic data can be analyzed by AI algorithms to predict accidents, optimize signal timings, and ease congestion [24]. By utilizing ontologies and semantic analysis to translate formats and protocols, AI-powered middleware can facilitate smooth data exchange between systems that would otherwise be incompatible [25]. An early warning system against cyberattacks is provided by AI tools like anomaly detection algorithms, which assist in identifying anomalous activity in networks. Differential privacy techniques can enable cities to analyze datasets without compromising individual privacy [26,27,28]. AI can support social inclusion by identifying underserved populations using geospatial and demographic data, thus enabling targeted interventions in health, education, and infrastructure development [29]. As a matter of fact, AI under the auspices of Blockchain technology is significantly transforming the housing, infrastructure, and real estate sectors in Nigeria, Egypt, and South Africa by promoting housing accessibility, restructuring property transactions, enhancing operational efficiency, promoting sustainability, and contributing to economic growth, as well as presenting several ethical and social bottlenecks that may require administrative accountability [30]. However, realizing their full potential requires proactive policymaking, ethical considerations, inclusive frameworks, and continued collaboration among governments, private sectors, and tech innovators [31].

In Nigeria, the potential benefits and implementation challenges create limitations over the use of artificial intelligence in developing smart cities. For instance, rapid urbanization seen in Nigeria frequently outpaces infrastructure development, resulting in significant strain on public services seen in areas of inadequate housing, inefficient transportation systems, and insufficient waste management [32]. However, there is strong agreement among urban dwellers regarding the positive impact of AI on efficient urban planning owing to AI's transformative potential in urban development [33]. Hitherto, there is need to implement intelligent transportation systems (ITS) which will utilize real-time data to optimize traffic flow, manage signals, and inform drivers about road conditions and alternative routes [32]. There is also need to emulate other countries of the world to implement non-motorized transport within our traffic management solutions, such as cycling and walking. This will help in enabling a suitable environment furnished with dedicated pathways for these purposes, thereby reducing the number of vehicles on the road. In Lekki area of Lagos, several estates offer smart living in rainwater harvesting, facial recognition security, and a community app powered by a collection of AI-driven tools that work through tech-driven urban lab, with IoT sensors, AI traffic systems, and solar-powered grids [34]. Along with the potential benefits of AI technology, there should be an ethical framework to guard against deliberate or inadvertent measures towards violating ethical norms particularly while utilizing AI-driven tools [35].

3. Methodology

This study adopted Agile methodology for the purpose of applying it into smart city development powered by AI-driven tools. This is enabled by the use of mixed-method of research in which qualitative and quantitative approaches are combined to gain a holistic understanding of how agile methodology supports smart city initiatives, particularly those involving AI tools, and further examine actual implementations. Agile methodology is suitable for this work because it has the capacity of providing a responsive framework that can be considered suitable for aligning well with the needs of urban innovation. For example, smart transportation, energy optimization, and citizen engagement platforms benefit from Agile's flexibility. Also, agile enables cross-functional teams comprising urban planners, software developers, data scientists, and policy makers. The cross-functional teams are meant to collaborate and deliver functional solutions quickly and swiftly. As a result, user stories collected from residents and stakeholders can be converted into tangible features within short iterations, allowing for real-world testing and feedback loops. This is especially critical in smart cities where decisions have direct societal impact and demand constant refinement. This study adopts agile to implement smart city suitable for Nigerian township using AI-driven tools as follows:

1. Establishing overall objectives for the smart city initiative.
   Definition factors: improving mobility, sustainability, safety, and public service delivery.
2. Analyzing existing structures and essential datasets available.
   Assessment parameters: traffic, energy, health, environmental data.
3. Ensuring team collaboration.
   Technical teams: AI specialists, urban planners, software developers, and civic leaders.
4. Identifying key use cases:

Design loci: smart waste management, predictive policing, adaptive traffic signals.
5. Using machine learning to train models using local data.
AI focus: predict peak traffic hours, adjust city signals dynamically.
6. Applying ethical AI principles.
Ethics compliance focus: data privacy, transparency, fairness, and accountability.
7. Evolving the smart city services continuously.
Feedback points: real-time performance monitoring, distributed feedback collection, and new plans.

Agile is particularly useful in this study because it has high adaptability to policy & data changes, high enablement for citizen involvement, excellent procedure for iterative AI model improvement, and good way of handling uncertain infrastructure. Hence, it is highly suitable for Nigerian urban dynamics.

3.1 Data Collection

This study utilized secondary data sourced from scholarly articles, case studies, and industry reports to extract key indicators related to Agile practices and AI functionalities. The data were gathered after conducting systematic literature review using two databases namely Google Scholar, and ResearchGate with specified keywords. The major activities in this process are:

1. **Extract** – Using API integration, appropriate structured metrics were extracted (e.g., power outage frequency, or traffic congestion).
2. **Transform** – On an appropriate scale (e.g., 0 to 1), metrics are normalized
3. **Load** – Normalized metrics are inserted into the NAI-SMART Knowledge Graph.

The normalized secondary data were used to validate the AI model in terms of accuracy using regression analysis. Python Pandas was used to crosscheck against Google Mobility data.

3.2 NAI-SMART Framework

This study proposed a framework tailored to Nigeria's socio-economic and infrastructural context which is titled NAI-SMART (Nigeria Agile Integration for Smart City Transformation). NAI-SMART comprises seven (7) phases that synergically provide a locally sensitive, iterative roadmap that fuses AI's transformative power with agile's adaptability, offering a path toward sustainable smart cities in Nigeria.

1. **Problem-Centric Discovery Phase**
This involves identifying the most pressing urban challenges in Nigerian cities: Community engagement, urban needs analysis, and data mapping.
2. **Agile AI Planning Phase**
This involves setting up a flexible, sprint-based strategy for AI solution development: Formation of Agile teams, sprint backlog, and MVP design.
3. **Data Infrastructure Layer**
This involves addressing infrastructural and technological constraints in Nigerian cities: IoT deployment, open data platforms, mobile-ready AI models.
4. **Iterative AI Model Development**
This involves building, testing, and adapting AI solutions (NAI-SMART Urban Intelligence Engine): Prototype, test, gather feedback, and optimize.
5. **Policy and Governance Alignment**
This involves ensuring regulatory and administrative support for implementation: Regulatory sandbox, ethical guidelines, training programs.
6. **Deployment and Sustainability Phase**
This involves deploying, monitoring, and continuously improving smart city solutions: Rollout of solutions, real-time dashboards, PPP-based funding.
7. **Evaluation and Knowledge Transfer**
This involves assessing impact and replicating success: Impact measurement, replication toolkit, public knowledge base.

The NAI-SMART Framework is visually represented in fig. 1. The diagram contains agile features as prominent components to reflect how it fosters scalable solutions in reducing risks, supporting innovation, and enhancing public trust by involving stakeholders throughout the process – local governments provide governance, funding, and policy backing; individual citizens co-create, validate, and monitor outcomes; while businesses drive innovation and scale through public-private partnerships. Stakeholder engagement in NAI-SMART is not peripheral. Instead, it is embedded in every phase of development. Table 1 shows stakeholders' involvement at various stages of NAI-SMART implementation.

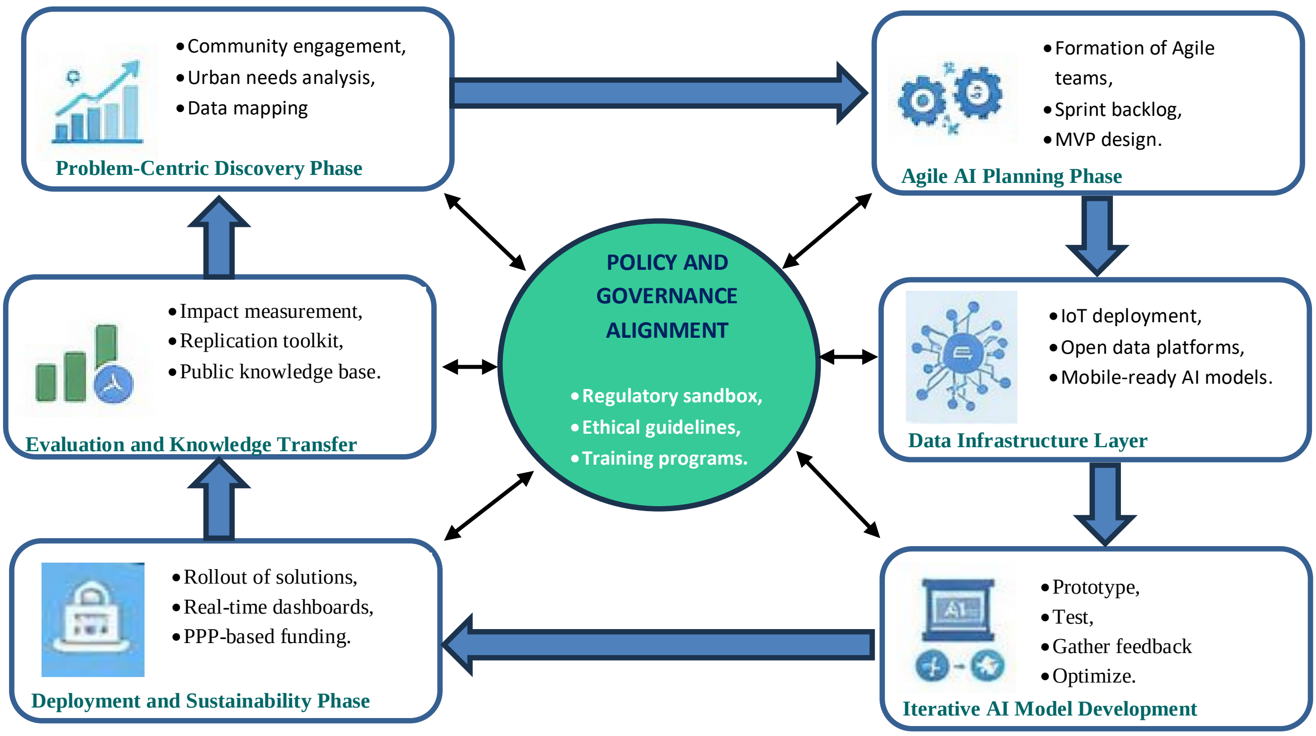

Fig. 1. NAI-SMART Framework

In Fig. 1, ethics and regulations from both industry and government policies form a central point in the NAI-SMART Framework for the purpose of coordinating other phases. This implies that every transformative process is check-mated by a number of rules in order to maintain ethical standards. This ensures that data are collected appropriately and are subjected to various preprocessing stages to maintain authenticity, accuracy, confidentiality, and integrity. The 1st phase captures user stories and stakeholder mapping which typically engage citizens, local authorities, and private sector in co-creation workshops for the purpose of gathering appropriate feedbacks. This creates room for initiating sprint backlog which forms the major part of the 2nd phase. Backlogging places priority on Minimum Viable Products (MVPs) for testing, for instance, a small-scale AI traffic model for one district. In the 3rd phase, continuous integration/continuous deployment (CI/CD) pipelines are created for real-time data ingestion and model retraining. This is the time when iterative sprints are utilized to deploy IoT sensors, open data APIs, and data lakes. This is done incrementally to ensure retrospective improvements on each sprint. The 4th phase involves building MVP AI models to predict or optimize city operations, such as waste collection routes or power outage forecasting. Continuous feedback is of high value at this stage in order to maintain Agile Machine Learning cycle: prototype → test → feedback → retrain → deploy. In the 5th phase, ethical checks are done using legal experts, regulators, and developers who collaborate to review regulatory sandbox environments for AI use. The 6th phase involves the use of sustainability metrics (such as energy use, cost savings, and satisfaction ratings) alongside integrated feedback dashboards for real-time monitoring and citizen reporting to assess the incremental rollouts. In the 7th phase, measurable indicators (such as service uptime, citizen satisfaction, and environmental improvement) are deployed in retrospective reviews for the purpose of highlighting performance gaps and inform next cycle improvements.

Table 1. Stakeholder engagement in NAI-SMART

Stage	Stakeholder Involved
Problem Discovery	Local government + Citizens
Co-Design Sprint	Developers + Citizens + SMEs
Policy Alignment	Government + Regulators
Implementation	AI teams + Private sector
Feedback Loop	Citizens + City Planners

3.2.1 NAI-SMART Urban Intelligence Engine (NAI-SMART UIE) Model

NAI-SMART UIE was modelled in loosely-coupled modules to perform the functions of traffic prediction, waste management routing, energy loading forecasting, and sentiment analysis on citizen feedback. This means that no module is affected whenever any of them is either temporarily or permanently inactivated. The model is created on a hybrid platform to accommodate rule-based and the machine learning features for the implementation of its modules. The AI tools involved are (Gated Recurrent Unit) GRU time series model, Reinforcement learning, XGBoost, and

Scikit-learn to implement the respective modules. The respective modules are visually represented in the high-level architecture shown in fig. 2. GRU has fewer parameters and is faster to train, a typical fit for the Nigerian situation where edge devices are limited. Hence, it can be hosted at edge gateways for low-latency control (such as adaptive signals) or in the cloud for city-level forecasts. Reinforcement learning learns to adapt to changing environments and can discover control strategies that outperform hand-tuned heuristics. Hence, it is chosen because it can optimize for long-term rewards (e.g., minimize city-wide delay or fuel use), not just single-step predictions, a necessary requirement for traffic signal control and routing. Risk-aware Reinforcement Learning algorithm helps the NAI-SMART UIE to enforce safety bounds (for instance, maximum queue length) and reduce risky explorations. XGBoost is used for tabular prediction and/or classification. This is important because many municipal datasets are tabular such as historical outages by substation, census data, and household attributes. Hence, XGBoost is essential for implementing energy load forecasting, outage risk, service prioritization, and anomaly detection in the model.

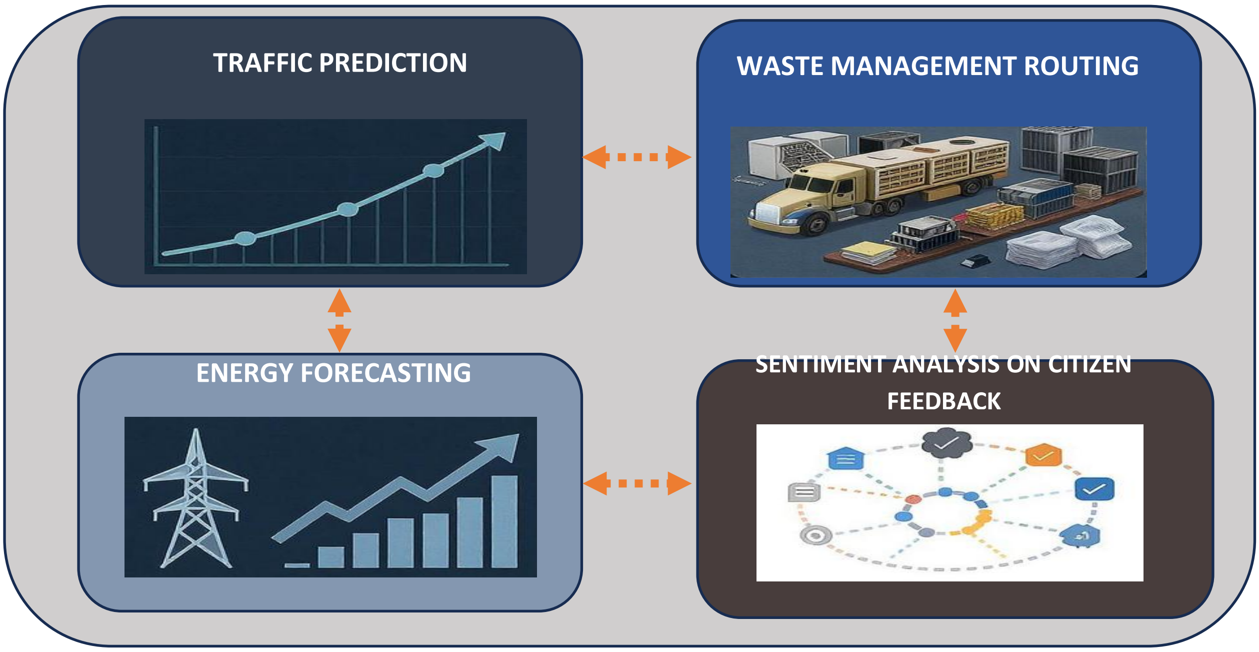

Fig. 2. NAI-SMART UIE Architecture

3.2.2 NAI-SMART UIE Model Training

NAI-SMART UIE model was made to predict a smart city efficiency score on the scale of 0 to100. The model is used iteratively for prototyping data-driven urban interventions, testing AI solution impact simulations, feedback gathering from civic platforms, optimization of infrastructure investment and policy alignment. The dataset (an extract from the Nigeria Bureau of Statistics) that was used in training NAI-SMART UIE is shown in table 2. The training was meant to make predictions based on the following six (6) parameters:

1. Traffic Congestion Index - TCI
2. Waste Collection Efficiency - WCE
3. Average Daily Power Outage (hours) - ADPO
4. Citizen Feedback Score - CFS
5. Population Density (specifically for a single tribe) - PD
6. Region Type - RT

A heuristic model equation was formulated (shown in equation (1)) using these parameters for the purpose of calculating the predicted smart city score (PSCS). The formulation was on the basis that the model yields better outcome in a situation when there is less traffic congestion, better waste efficiency, penalty for higher power outages, civil satisfaction, and better infrastructure efficiency following a higher population density.

$$PSCS = (1-TCI)*25 + WCE*20 + \max(0,(5-ADPO))*5 + CFS*10 + \left(\frac{\min(PD,15000)}{15000}*10\right)*RT \quad (1)$$

Table 2. Training Dataset

Location	Traffic Congestion Index	Waste Collection Efficiency	Average Power Outage (hours)	Citizen Feedback Score	Population Density	Region Type
Kano	0.33	0.24	4	4.7	4,965	Semi-Urban
Ibadan	0.91	0.85	7	2.3	12,100	Semi-Urban
Enugu	0.56	0.80	11	4.7	3,879	Semi-Urban

4. Findings and Discussion

4.1 Model Evaluation

The NAI-SMART UIE model was later evaluated using the test dataset shown in table 4. The model used a heuristic model formula based on weighted metrics (as shown in table 3) to calculate the scores which can then be measured according to the scale of 0 to 100. The predicted scores also form part of table 3.

Table 3. Model Metrics and associated Weights

Metric	Weight
Traffic Congestion Index	0 to 1; lower is better
Waste Collection Efficiency	0 to 1; higher is better
Average Power Outage Hours per day	0 to 12; lower is better
Citizen Feedback Score	1 to 5; higher is better
Population Density	people/km ²
Region Type	Urban = 1.0, Semi-Urban = 0.9; multiplier for local constraints

Table 4. Test Dataset and Predicted Output

Location	Traffic Congestion Index	Waste Collection Efficiency	Average Power Outage (hours)	Citizen Feedback Score	Population Density	Region Type	Predicted Smart City Score (PSCS)
Abuja Central	0.60	0.64	0	5.0	6,288	Semi-Urban	**91.79**
Enugu Urban	0.62	0.87	0	2.4	13,181	Urban	**84.69**
Lagos Mainland	0.90	0.78	10	4.3	9,129	Urban	**42.19**
Ibadan City	0.91	0.85	7	2.3	12,100	Semi-Urban	**36.29**
Kano Metro	0.33	0.24	4	4.7	4,965	Semi-Urban	**69.17**

The output of the model namely the predicted smart city score is visually represented using a bar chart shown in fig 3. These outputs create a transcending trajectory (see fig 4) away from the federal capital Abuja which obviously have the highest level of digitization so far in Nigeria. This trajectory also shows that the father you move from the northern region, where the federal capital is located, the less digitization you notice among different cities in Nigeria.

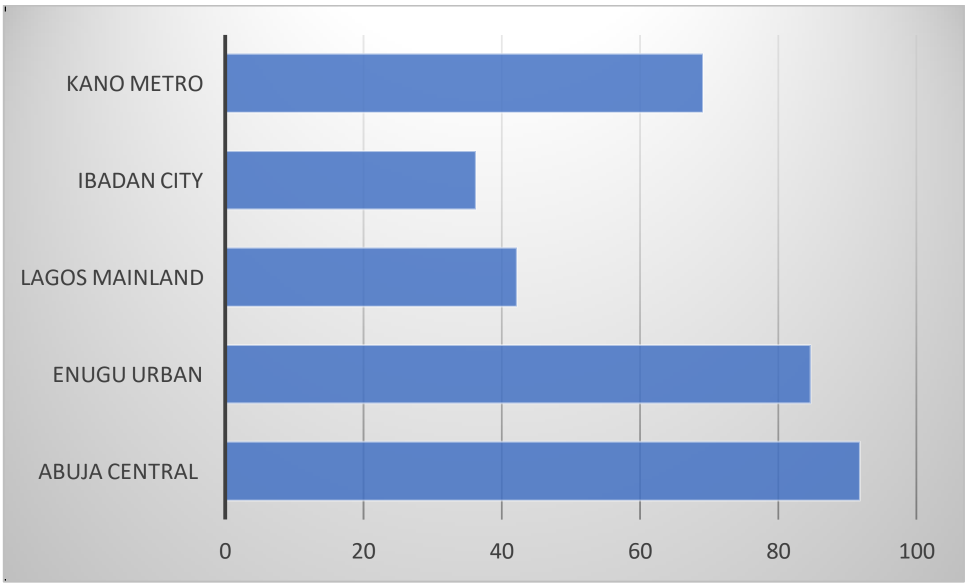

Fig. 3. Smart City Prediction Outputs

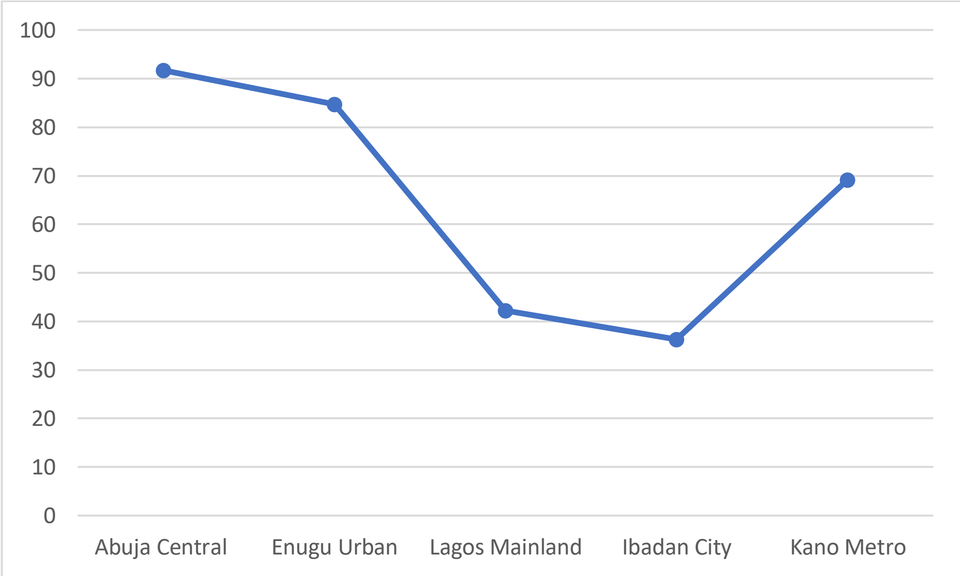

Fig. 4. Smart City-readiness Trajectory

4.2 Model Evaluation Metrics

The NAI-SMART UIE combines multiple AI tools serving different urban functions. Hence, no single metric is sufficient. Each tool's evaluation metric must align with its objective and data type (continuous, categorical, or sequential) as shown in table 4. The evaluation is done in three layers namely Model Layer (AI Tools), System Layer (UIE Dashboard), and Policy Layer (Impact Metrics) to ascertain the extent at which the outputs match with the real time target outcomes.

Table 5. Evaluation Metrics per AI-Tool

AI- Tool	Implementation Purpose	Metrics	Evaluation Purpose	Justification
GRU	Time-series forecasting (namely predicting traffic flow, power demand, waste volume)	MAE, RMSE	Measures continuous prediction accuracy i.e., lower errors = better forecasts.	MAE, RMSE are interpretable by city planners for energy and traffic prediction.
XGBoost	Classification/prediction tasks (namely identifying high-risk infrastructure zones or outage probabilities)	F1-score, ROC-AUC, Accuracy	Evaluates correct predictions and balances false positives/negatives.	Data imbalance (common in Nigeria) makes F1-score and ROC-AUC more reliable than plain accuracy
Reinforcement Learning	Decision-making and control optimization (namely adaptive traffic light scheduling, waste truck routing)	Cumulative Reward, Policy Efficiency	Evaluates long-term performance, stability, and learning behaviour over episodes.	Cumulative reward reflects long-term improvement; Policy efficiency aligns with Agile's iterative feedback loops.

Table 6. Layered Evaluation Across NAI-SMART UIE

Evaluation Layer	Metrics Used	Evaluation Outcome
Model Layer	MAE, RMSE, F1, ROC-AUC, Cumulative Reward	Predictive reliability and decision accuracy
System Layer	Response time, data latency, dashboard uptime	Operational stability
Policy Layer	Efficiency gains (%), CO_2 reduction, citizen satisfaction index	Real-world effectiveness and sustainability

NAI-SMART UIE can be deployed either in the cloud or on local systems. In cloud deployment, the system can leverage elastic computing resources from platforms which can automatically scale up or down based on demand [36]. This is particularly beneficial for rapidly growing Nigerian urban areas like Abuja, Lagos, and Kano, where data volumes from IoT devices, sensors, and social platforms fluctuate significantly. On the other hand, deploying NAI-SMART UIE locally would offer improved control over data privacy, localized AI processing, and offline functionality. This is crucial in Nigerian cities where intermittent network outages could affect cloud performance [37]. By implementing edge AI nodes within municipal servers or local data centres, NAI-SMART UIE can process and store data near its source. On this premise, it is recommended to deploy NAI-SMART UIE using a hybrid approach, whereby time-sensitive control loops are operated locally at the edge (via renewable-backed edge infrastructure) while using cloud backends (modular microservices and MLOps pipelines) for heavy model training, cross-city analytics, historical data archives, and system orchestration. The hybrid model also supports phased rollouts consistent with Agile sprints. This ensures that the NAI-SMART framework evolves with urban growth, policy changes, and emerging technologies.

5. Conclusion

As urbanization accelerates and the demand for liveable, sustainable cities increases, smart city development remains a key strategic priority. Although certain challenges are imminent, making the road to building truly smart cities complex. However, the judicious application of AI technologies can catalyse progress and help cities meet the demands of the 21st century. This paper had therefore shown that there is paramount need for a paradigm shift from technology-centred development to human-centred smart cities, in order to harness the essential potentials of artificial intelligence.

The NAI-SMART Framework presented in this work showed that the integration of AI-driven tools in Nigerian urban centres holds great potential to transforming these cities into world-needed smart cities particularly in the areas of managing traffic congestion, monitoring environmental pollution, ensuring efficient power distribution, and improving citizen engagement through intelligent platforms.

The NAI-SMART UIE Model showed that the potentiality is higher in some cities than others. Results from the model proved that Abuja, Enugu, and Kano are technologically ready for smart city development whereas places like Ibadan and Lagos Mainland yet require more digitization to create enabling environment for smart transformation. This establishes the fact that NAI-SMART has the potentiality of sustaining higher levels of scalability, public engagement, and solution effectiveness via mitigating the risks associated with large-scale deployments by enabling continuous feedback and incremental innovation.

6. Recommendations

The need for digital technologies to speed up the drive towards addressing the pressing challenges of urbanization for the purpose of improving the lives of city dwellers cannot be over-emphasized. This study therefore recommends that advancement be made in the analysis of the level of digital-compliance of more cities in Nigeria to cut across the entire regions of the nation. This will position artificial intelligence and machine learning at the point of achieving smart cities that truly serve the public interest. Future work can be directed towards the perspective of deploying other research methodologies through a phased and timed process to ascertain the efficacy of their fusion with AI-driven tools for building smart cities. Leveraging evolving technologies and tools, ethical policies to address technicalities and AI governance should be created and sustained to check excesses particularly in harnessing the potentials of artificial intelligence.

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