SELINUS UNIVERSITY
OF SCIENCES AND LITERATURE

Monitoring Routine Immunization Program Progress Using Acute Flaccid Paralysis (AFP) Data

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A THESIS

Presented to the Department of
Public Health
program at Selinus University

Faculty of Natural Health Science
in fulfillment of the requirements
for the degree of Doctor of Philosophy in
Public Health
2025

Acknowledgement

First and foremost, I offer my deepest gratitude to my God who gave me the strength and resilience to complete the thesis for PhD. I would like also to express my special appreciation to Dazi Victor who played a significant role for the data analysis and finalization of the document. My supervisor, Prof. Salvatore Fava, whose insightful guidance, unwavering support, and invaluable feedback were instrumental in shaping this research from its inception to completion. Further, the technical support I received from my work colleague, Dazi Victor, in data analysis and reviewing the paper was highly appreciated. I am also immensely grateful to the members of the dissertation committee for their expert critiques and knowledge

I extend my thanks to my children, Neftalem Tesfaye Bedada and Bethel Tesfaye Bedada, for the encouragement, understanding, and constant moral support that made the process more bearable. This research would not have been possible without the continued moral support from my children.

Finally, I want to thank my dear wife, Rahel Solomon Habtew, for her support and encouragement through all the ups and downs of this long journey. Your belief in me kept me going forward. This work is dedicated to my wife.

Abstract

Background: Reliable, timely estimates of routine immunisation (RI) remain difficult in Nigeria, where administrative DHIS2 data, household surveys (NICS/MICS), and surveillance indicators often differ. Using Acute Flaccid Paralysis (AFP) case-based surveillance may offer near–real-time insights into Oral Polio Vaccine (OPV) coverage, zero-dose prevalence, and poliovirus risk, particularly in underserved and conflict-affected areas.

Objectives: This study aimed to assess how closely AFP-derived OPV coverage matches NICS estimates at national and subnational levels; to quantify and map the burden of zero-dose children and their inequalities by location, gender, residence, and nomadic status; and to develop and validate predictive models that connect AFP indicators, NICS coverage, reported AFP cases, and zero-dose burden to classify Local Government Area (LGA) risk and predict RI coverage for programme planning.

Methodology: A descriptive cross-sectional analysis utilised 2022 AFP microdata (n=7,613 of 10,491 cases), NICS 2022 coverage, and RI (OPV0–OPV3) reports for 2022–2024. Inequality analyses were stratified by sex, zone, residence, and nomadic status. Associations were evaluated using Pearson/Spearman correlations and linear regression. Classification employed a random forest (500 trees) to categorise LGAs as Low/Medium/High burden. Time-series (ARIMA) and mixed-effects models, based on NICS 2022, were used to adjust RI trends and forecast 2025 coverage.

Findings: AFP-derived OPV3 closely aligns with NICS nationally (gap ≈0.2 pp in 2021), with wider subnational variation. Zero-dose and AFP suspected cases are strongly associated ($r=0.733$; Spearman $\rho=0.683$; $p<0.001$). In regression analysis, each additional zero-dose child (24–35 months) corresponds to approximately 4.67 more AFP suspected cases ($R^2=0.537$; $p<0.001$). Random-forest internal validation achieves 82% accuracy overall (OOB error 17.9%), with the best performance in Low-burden LGAs and identifying clusters of high-risk LGAs—often border areas and high zero-dose regions. Inequities persist by zone and residence (e.g., urban–rural gaps), and nomadic settlements show markedly lower full-dose completion. ARIMA projects the 2025 national OPV3 to be around 55% (remaining within 80–95% CIs).

Conclusions: AFP surveillance can effectively complement NICS for RI monitoring and early risk detection, enabling more detailed, near-real-time targeting of zero-dose hotspots. Combining AFP, NICS, and RI data streams, along with routine use of predictive analytics, can enhance microplanning, prioritise high-risk LGAs, and speed up progress towards poliovirus interruption—while ongoing improvements in data quality and equity-focused delivery remain vital.

Keywords: Routine Immunisation Coverage, Acute Flaccid Paralysis Surveillance, Zero-Dose Children, Predictive Modelling

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CHAPTER 1: INTRODUCTION AND AIM OF STUDY

1.1. Background of Study

The quality of DHIS2 (District Health Information Software 2) and Routine Immunisation (RI) administrative data has significantly improved(Etamesor et al., 2018). This positive trend is evident from the decreasing gap when comparing these administrative data with results from the Multiple Indicator Cluster Surveys (MICS) or the National Immunisation Coverage Surveys (NICS)(Daley et al., 2024; NBS et al., 2022; Wolter et al., 2017). The Routine Immunisation coverage survey, considered the most trustworthy data source, is carried out periodically, every 3–5 years, rather than annually, which limits planning and monitoring purposes.

In 2022, the international organisation partners offered technical assistance, with government counterpart funding and financial contributions from UNICEF, Gavi, the Vaccine Alliance, and the Bill & Melinda Gates Foundation (BMGF) to conduct a nationwide MICS(NBS et al., 2022). This survey presents statistically valid and internationally comparable data crucial for crafting evidence-based policies and programmes and tracking progress regarding missed opportunities for vaccination (MOV) in Nigeria(NBS et al., 2022).

The administrative data, which is available annually, has limitations due to underestimated population projections and unreliable reporting of administrative data. Despite high administrative coverage, the resurgence of infectious disease outbreaks across various regions was registered(Dunkle et al., 2014; Harrison et al., 2020). Notably, one of the most concerning outcomes of this outbreak is the re-emergence of the Variant Polio Virus type 2 in the African

Region(Alleman et al., 2023; Dowdle et al., 1999; Endegue-Zanga et al., 2015; Etsano et al., 2016; Fernandez-Garcia et al., 2018; Hamisu et al., 2018; Jenkins et al., 2010; Lorenzetti et al., 2023; Mbaeyi et al., 2021; Morais et al., 2023; Odoom et al., 2024; Odoom et al., 2021; Voorman et al., 2024).

This situation highlights the critical issue of reliable and timely coverage rates for the Oral Polio Vaccine (OPV) and Inactivated Polio Vaccine (IPV), particularly in under-resourced areas with challenging geography and terrain, which are affected mainly by conflict(Agócs et al., 2021; Alegana et al., 2024; Arambepola et al., 2021; Bawa et al., 2019; Bogale et al., 2025; Gebremedhin et al., 2023; Ishoso et al., 2023; Maleghemi et al., 2022; Mbaeyi et al., 2021; Wasswa et al., 2025).

Moreover, inaccurate and incomplete data, which are some factors of the larger social determinants of health, have hindered efforts to understand immunisation coverage, especially in low- and middle-income countries (LMIC)(Harrison et al., 2020). The expanded programme on immunisation (EPI) and the global vaccine action plan (GVAP) were developed to promote equitable access to immunisation as a primary global vision(Bawa et al., 2018; Cherian & Mantel, 2020; Harrison et al., 2020).

Therefore, in 2016, the World Health Organisation (WHO) advised administering at least one dose of IPV before starting routine immunisation with OPV. This strategy aims to interrupt vaccine-associated paralytic polio (VAPPs) and Variant Polio Virus (VPVs) through targeted immunisation activities(Ciapponi et al., 2019). Nonetheless, many missed immunisation opportunities have hindered achieving the global coverage targets the World Health Organisation set. Identifying gaps that clarify the true coverage of the Polio Vaccine and pinpointing potential polio reservoir areas can significantly aid in interrupting the variant polio virus in Africa, and more

specifically in Nigeria(Abrams et al., 2013; Bawa et al., 2018; Bogale et al., 2025; Ciapponi et al., 2019).

AFP surveillance and vaccine coverage are primary predictors of the outcome of the variant polio virus in Nigeria. The National Emergency Operational Centre 2021 polio feedback reported a decrease in the number of polio outbreaks in the northernmost part of Nigeria, from 1028 to 170 confirmed cases in 2022. This highlights the importance of robust data management and analysis for AFP case-based surveillance and MICS/NICS data in identifying polio vaccine immunisation coverage gaps and effectively planning interventions to address these immunity gaps.

The polio program systematically collects Acute Flaccid Paralysis (AFP) data through a robust case-based surveillance system(GPEI, 2023; WHO, 2021b). This comprehensive approach incorporates Oral Polio Vaccine (OPV) derived from both Supplementary Immunisation Activities (SIA) and Routine Immunisation (RI) efforts. The data generated from OPV administered in RI is crucial in providing valuable insights that are instrumental for monitoring progress, identifying gaps, strategic planning, and making informed, evidence-based decisions regarding polio eradication efforts. This vision is also enshrined in the Global Polio Eradication Initiative (GPEI) publication on Acute Flaccid Paralysis (AFP) case-based surveillance, which lies in its comprehensive approach to understanding and monitoring vaccine coverage, particularly in Low- and Middle-Income Countries (LMIC).

This thesis emphasises the vital role of AFP surveillance in monitoring immunisation rates, analysing demographic data by age group, and modelling suspected AFP cases alongside vaccination efforts from routine immunisation and SIAs data. Since WHO and GPEI analyses often use non-polio AFP (NP-AFP) as the surveillance quality indicator, the researcher has utilised

vaccine coverage estimation, the number of cases from AFP data, which is based on all detected suspected cases, not just confirmed polio cases, to build a predictive model(Amodan et al., 2022; Korukluoglu et al., 2021; Umutesi et al., 2023).

It underscores its importance in identifying gaps in coverage, ensuring that vulnerable populations are adequately protected against poliovirus transmission(GPEI, 2023). The goal is to identify gaps in immunisation, risk patterns in LGAs with low vaccine coverage and high AFP suspicion, pinpoint hotspot LGAs with greater outbreak risk, and create predictive models to focus surveillance efforts. The study also assesses the consistency of reported OPV and RI coverage using 2022 Nigeria AFP data, analysing vaccination status across five proxy age groups with a sample of 7613 out of the total population, 10491. This information supports the government and partners in their annual monitoring and strategic planning to improve routine immunisation and promote equity.

Using a cross-sectional descriptive approach, the study compares vaccine coverage estimates from AFP surveillance and NICS data, explores their link with reported AFP cases and zero-dose prevalence, and develops a statistical model to predict coverage based on AFP indicators. These findings will guide evidence-based recommendations for integrating AFP immunisation data into Nigeria's routine EPI monitoring, aiming to minimise missed opportunities for vaccinations and enhance the performance of the RI programme. The following section describes the statement of the problem.

1.2. Statement of the Problem

Routine Immunisation (RI) remains a key pillar of public health in Nigeria, essential for preventing vaccine-preventable diseases (VPDs)(Adamu et al., 2024; Agócs et al., 2021). Despite advances in expanding immunisation services, coverage is still inadequate in many areas, with ongoing geographic and socio-economic inequalities(Apeng et al., 2010). These gaps lead to many children being under-immunised or fully unvaccinated, known as "zero-dose" children, which heightens their risk of VPD outbreaks and hampers national disease control efforts(Alegana et al., 2024; Arambepola et al., 2021).

Monitoring the performance of RI programmes in Nigeria has traditionally depended on three primary data sources: administrative data from the District Health Information System (DHIS2), household surveys like the National Immunisation Coverage Survey (NICS), and additional campaign monitoring(WHO & UNICEF, 2021). Each source, however, has its limitations. DHIS2 data can be affected by over- or under-reporting resulting from inaccurate target population estimates, data entry mistakes, or inconsistent reporting completeness. Household surveys provide valuable population coverage data but are conducted only periodically and may suffer from recall bias, which hampers their timeliness for programme decisions.

Acute Flaccid Paralysis (AFP) surveillance, mainly established as part of the Global Polio Eradication Initiative (GPEI), offers a valuable and often underused source of immunisation data(WHO, 2021b). During AFP case investigations, vaccination histories, especially oral polio vaccine (OPV) doses received through both routine immunisation (RI) and supplementary immunisation activities (SIAs), are systematically gathered. This provides an opportunity to use AFP case-based surveillance as a proxy to monitor RI performance, identify coverage gaps, and track missed opportunities for vaccinations in near-real time.

Limited evidence exists on how well vaccine coverage estimates from AFP data align with those from other sources, like NICS or administrative reports. Additionally, AFP datasets include information on zero-dose children and the geographic spread of under-immunisation, which can be used in statistical models to identify low-coverage areas and guide targeted interventions.

In the context of post-polio eradication transition planning, integrating AFP-based immunisation monitoring into the broader EPI performance review framework could enhance surveillance sensitivity, optimise resource allocation, and ensure timely corrective actions. However, to make this integration policy-relevant, it is necessary to rigorously assess the validity, strengths, and limitations of AFP-derived vaccine coverage estimates compared to established sources, and to explore their potential for predictive modelling.

1.3. Research Questions

1. What is the level of routine immunisation coverage reported in the AFP surveillance data compared to the NICS estimates for Nigeria in 2022?
2. What percentage of zero-dose children are detected via AFP surveillance, and how does this differ across regions?
3. What is the predictive link between vaccine coverage (from NICS), AFP-reported suspected cases, and zero-dose children in assessing RI performance at subnational levels?

1.4. Objectives of the Study

Using AFP case-based surveillance data offers crucial insights into vaccine coverage when investigating suspected AFP cases, as these areas can be hotspots for polio transmission. Therefore, the main objective of this research is to evaluate and model the progress of routine immunisation programmes in Nigeria using 2022 AFP case-based surveillance and NICS vaccine coverage data.

Specific Objectives

I. Compare vaccine coverage estimates from AFP surveillance data with those from NICS across Nigeria and at subnational levels.

II. To assess the proportion and geographic spread of zero-dose children using AFP surveillance data.

III. To develop a statistical model for predicting RI coverage using AFP surveillance indicators, NICS coverage estimates, reported AFP cases, and zero-dose prevalence.

1.5. Significance of the Study

This study has important implications for immunisation monitoring, policy, and practice in Nigeria and similar low- and middle-income countries. By using AFP surveillance data, which offers nationwide coverage, established quality control, and regular reporting, this research introduces a novel and practical method to supplement existing vaccine coverage monitoring systems.

Incorporating AFP-derived immunisation indicators into routine Expanded Programme on Immunisation (EPI) performance reviews could yield more frequent, near-real-time insights into vaccination coverage, allowing for quicker identification of under-immunised and zero-dose populations. Unlike household surveys such as NICS, which are conducted periodically and demand significant resources, AFP surveillance functions continuously, offering the potential for more prompt interventions.

By comparing AFP-derived coverage estimates with NICS data, the study will help evaluate the validity and reliability of AFP data for immunisation monitoring. This comparison will also underline the strengths and limitations of AFP surveillance as a secondary source for vaccine coverage measurement, ensuring evidence-based decision-making regarding its use in national and subnational immunisation programme assessment.

The modelling part of this study provides additional predictive insights. By applying statistical models to connect AFP surveillance data, NICS vaccine coverage, reported AFP cases, and zero-dose prevalence, health managers can forecast regions at risk of low coverage. These predictive tools could improve microplanning, direct targeted supplemental immunisation campaigns, and optimise how resources are distributed to underserved areas.

In polio eradication transition planning, highlighting the benefits of AFP data beyond poliovirus detection reinforces the importance of maintaining this surveillance system for wider public health advantages. Ultimately, this study aims to enhance immunisation coverage, address inequities, and safeguard children from vaccine-preventable diseases.

This study examines the progress of the routine immunisation (RI) programme in Nigeria, utilising 2022 Acute Flaccid Paralysis (AFP) case-based surveillance data. It specifically focuses

on the Oral Polio Vaccine (OPV) and other antigens from the Expanded Programme on Immunisation (EPI). Using a descriptive cross-sectional approach, the research compares immunisation coverage indicators from AFP surveillance with data reported in the National Immunisation Coverage Survey (NICS) and administrative RI figures from the District Health Information System 2 (DHIS2).

1.6. Scope of the Study

- Data Sources – AFP case-based surveillance datasets for 2022, NICS 2022 national and subnational coverage estimates, and DHIS2-reported RI coverage data.
- Coverage includes all 36 states and the Federal Capital Territory, with detailed analysis at both state and Local Government Area (LGA) levels.
- Indicators include coverage of OPV and other selected antigens, missed opportunities for vaccination (MOV), and zero-dose prevalence.
- Analytical Approach – Utilises descriptive statistics to identify gaps in immunisation coverage, compares estimates from different data sources, and employs modelling to forecast vaccine coverage based on AFP-derived indicators, reported AFP cases, and zero-dose prevalence.
- Time Frame – The analysis will cover data gathered from January through December 2022.

The study will not gather new data directly but will depend solely on existing secondary data. While mainly focused on Nigeria, the results are intended to offer insights applicable to other African countries with AFP surveillance systems. The scope is limited to examining how AFP surveillance data can support RI programme monitoring and in modelling coverage trends, rather than evaluating clinical outcomes of AFP cases or performing biological sampling.

1.7. Limitations of the Study

Although this study offers useful insights into the potential of AFP surveillance data for tracking immunisation programme progress, it is important to recognise several limitations.

I. First, variations in data quality across sources can impact comparability. AFP surveillance data, NICS estimates, and DHIS2 administrative reports are gathered using different methodologies, time frames, and verification processes. AFP vaccination status is often determined by caregiver recall or health card checks during case investigations, which can lead to recall bias or misclassification. Although NICS data are more rigorously sampled, they are collected periodically and may not perfectly match AFP data timelines. Administrative RI data may also be affected by reporting inaccuracies, such as over-reporting or under-reporting by health facilities.

II. Second, there are representativeness concerns because AFP surveillance mainly focuses on children under 15, especially those under 5, and cases are not randomly spread across the population. This could restrict how well AFP-derived coverage estimates reflect the entire target population for routine immunisation.

III. Third, the cross-sectional design restricts causal conclusions. While it is possible to describe and model associations between AFP indicators, NICS coverage, and zero-dose prevalence, this study does not prove a direct cause-and-effect relationship between low coverage and AFP incidence.

IV. Fourth, limitations of the modelling approach need to be acknowledged. Predictive accuracy relies significantly on the quality, completeness, and compatibility of the

datasets. Factors like unmeasured confounders, such as local outbreak response efforts, community health worker performance, or sociopolitical disruptions, may affect vaccination coverage but might not be sufficiently recorded in the data used.

V. Fifth, data availability limitations might restrict the analysis scope. Disaggregated NICS data at the state and LGA levels could face access restrictions, and AFP datasets might have missing or incomplete vaccination histories for some cases.

VI. Finally, while the study aims to inform programme decision-making, challenges in translating policy may occur if stakeholders view AFP surveillance as a non-traditional tool for immunisation monitoring, requiring advocacy to gain acceptance.

Despite these limitations, combining data from various independent sources and using strong analytical and modelling methods enhances the reliability of the results and their usefulness for improving immunisation programs in Nigeria and elsewhere.

1.8. Operational Definition of Terms

The researcher, for this cross-sectional review or study, will adopt and utilise the following operational case definitions of terms and keywords. These definitions are specifically formulated to ensure clarity, consistency, and precision throughout the research process. They will guide the identification, classification, and analysis of data related to the study, thereby facilitating accurate interpretation and reliable results.

1. Acute Flaccid Paralysis – A clinical symptom that affects children below 15 years of age with a sudden onset of weakness or paralysis of the lower or upper limbs. Also,

conceptualised as any person whom a clinician suspects of being infected with poliovirus(Ali et al., 2023).

2. Case-based Surveillance - A surveillance following standard case definitions, case surveillance captures information that public health officials can use to understand where diseases are occurring, how they can be prevented, and which groups are most heavily impacted(Eales et al., 2024).

3. Immunisation - According to the WHO, this study conceptualises immunisation as the process by which individuals are protected against vaccine-preventable diseases through the administration of vaccines (Ahonkhai et al., 2022).

4. Routine Immunisation - Routine immunisation is the foundation through which countries provide access to lifesaving vaccines and control and eradicate vaccine-preventable diseases. It is the process of timely vaccination regularly, with vaccines considered important for a given country to reduce morbidity and mortality(WHO, 2025a).

5. Vaccine Coverage - Vaccine coverage refers to the proportion of a population that is appropriately immunised against a specific vaccine-preventable disease (VPD) (Matthew et al., 2024).

6. National Immunisation Coverage Survey and Multiple Indicator Cluster Survey - This is a household survey developed by UNICEF to assist countries in filling data gaps for monitoring human development indicators in general and the situation of children and women, in particular (UNICEF, 2018; WHO & UNICEF, 2021).

CHAPTER TWO: LITERATURE REVIEW

2.3.1 Introduction

The case-based surveillance data for Acute Flaccid Paralysis (AFP) continues to serve as a crucial validation tool for assessing the accuracy of routine immunisation administrative coverage (Cherian & Mantel, 2020). Over the past several years, Nigeria, along with numerous other countries, has increasingly depended on the Multiple Indicator Cluster Survey (MICS)(WHO & UNICEF, 2021). MICS is a comprehensive household survey developed by UNICEF designed to address data deficiencies in monitoring various human development indicators, including vaccine coverage.

This survey provides detailed insights that complement and validate existing immunisation data, thereby enhancing the reliability of health monitoring systems and informing targeted interventions to improve immunisation programs. MICS/NICS data provide the basis for improved planning at the country level and support the design of interventions at the sub-national level via the understanding of the actual performance or program impact over a period. However, due to funding limitations, this survey occurs every 3-5 years(WHO & UNICEF, 2023).

The need for a readily available and efficient alternative or supplement to the existing NICS (National Immunisation Coverage Survey) and MICS (Multiple Indicator Cluster Surveys) systems is critically important for effective annual planning and setting strategic public health priorities. In Nigeria, as well as in many other countries across Africa, AFP (Acute Flaccid Paralysis) case-based surveillance plays a vital role in verifying suspected poliovirus cases.

This surveillance provides comprehensive data on the vaccination history of affected individuals, including details about vaccines received, such as the oral polio vaccine (OPV) and the inactivated polio vaccine (IPV) via demographic and health survey (Idris et al., 2022; Wasswa et al., 2025). These vaccines are administered through routine immunisation programmes integrated within the national health system, as well as through supplementary immunisation activities (SIAs) designed to boost immunity in the population and quickly address immunisation gaps. Such surveillance systems are essential for monitoring vaccine coverage, identifying areas with low immunisation rates, and guiding public health interventions aimed at eradicating poliovirus and other preventable diseases.

The study has conducted a thorough examination of how administrative data can be effectively validated by using proxy data derived from AFP-OPV coverage, specifically among children under five, as supported by research conducted by Technical Working Groups (Scobie et al., 2020). This age group is recognised as the polio high-risk cohort, which is vital for targeted public health interventions. The validation process includes verifying data for suspected cases to ensure accuracy and reliability.

Such detailed analysis not only improves understanding of data validity but also provides timely and effective predictors for assessing immunisation outcomes and coverage across different age groups. Acknowledging the importance of a strong theoretical foundation, this section also reviews relevant literature discussing key concepts and terms related to the research. This review aims to situate the study within existing scholarly work, offering insights into previous methodologies and findings in the field of immunisation surveillance and data validation. Moving forward, the next section will concentrate on an in-depth review of immunisation.

2.3.2. Overview of Immunisation

Immunisation represents one of the most cost-effective means to improve the health and well-being of populations and contribute to the interruption of Infectious diseases such as Acute Flaccid Paralysis(Cherian & Mantel, 2020). Since the inception of the Expanded Programme on Immunisation (EPI) in 1974, considerable gains have been made in improving access to vaccination in all countries(Cherian & Mantel, 2020; Shattock et al., 2024).

EPI was established to significantly broaden the large-scale distribution of vaccines targeting six more life-threatening or disabling diseases: tuberculosis, diphtheria, tetanus, pertussis, poliomyelitis, and measles (Cherian & Mantel, 2020). The gradual rise in coverage following the establishment of EPI led to the launch of the Universal Childhood Immunisation (UCI) initiative, spearheaded by UNICEF in partnership with the World Health Organization (WHO) in 1984. The goal was to boost DTP3 coverage to 80% worldwide by 1990.

The initiative was highly successful, with global DTP3 coverage increasing from about 20% in 1980 to nearly 80% in 1990. In low-income countries, coverage rose from less than 10% in 1980 to 51% 1990. In 1980, worldwide coverage with three doses of Diphtheria–Tetanus–Pertussis (DTP) vaccines (DTP3) was around 20%, but there were significant disparities between high- and low-income countries; notably, coverage in low-income countries was under 10% (Cherian & Mantel, 2020). Vaccines already prevent more than 4.3 million deaths every year – but they have the potential for an even greater impact. Every dollar invested in immunisation programmes in 94 low- and middle-income countries over the next decade will return more than US$52 by lowering treatment costs, boosting productivity, and reducing long-term disability (IA2030, 2024). Child immunisation serves as a crucial entry point to a broad range of other essential health services, such as nutrition, development, and disease prevention.

Therefore, expanding immunisation efforts not only protects individual children but also contributes to the development of sustainable and resilient primary health care systems capable of serving entire communities (IA2030, 2024). To extend the benefits of routine immunisation to people of all ages, significant innovations are needed in delivery strategies, including community outreach, mobile clinics, and integrated health services.

Additionally, substantial investments are required to develop scalable and resilient vaccine logistics, including robust supply chains, advanced infrastructure, and modern manufacturing capabilities, ensuring vaccines reach even the most remote and underserved populations efficiently. Achieving universal immunisation coverage demands a global commitment to fully vaccinate every child on Earth, an imperative that involves mobilising resources, strengthening health systems, and fostering international cooperation (Abdallah et al., 2024).

Rapid, coordinated action is essential to overcoming the setbacks caused by the COVID-19 pandemic, which has delayed progress and left many children unprotected. The first year of the Coronavirus disease (COVID-19) pandemic registered the highest number of children under the age of one year who did not receive basic vaccines since 2009. This global health inequity results in less than a 20% chance that a child will be fully vaccinated by age 5.

Evidence of its impact on disrupting the expanded immunisation programme at the national level in 2020 is mounting; by the first quarter of 2022, measles cases in Africa had increased by 400% (17,500) compared to the same period in 2021 (Bellizzi et al., 2022). Inequalities caused by pandemics and other development challenges in LMICs have led to poor coverage and low-quality data.

Reaching every child in the district or community with immunisation services requires a comprehensive and well-coordinated programme that specifically aims to overcome the numerous barriers preventing access. These barriers can include geographical challenges, socio-economic factors, cultural beliefs, misinformation, and logistical issues, all of which contribute to the rising number of under-immunised or zero-dose children. In many countries, such as the Solomon Islands, the Momase Region of Papua New Guinea, the introduction of the Reaching Every District (RED) strategy, initially developed and recommended by the World Health Organisation (WHO), has been adopted and adapted by local health authorities (Angessa et al., 2024; Apeng et al., 2010). This strategy provides a systematic approach to identify coverage gaps, strengthen health systems, and address the specific challenges faced in each context, thereby improving immunisation coverage and ensuring that no child is left behind due to these barriers.

The World Health Assembly has endorsed the Global Vaccine Action Plan (GVAP), which aims for every child to have access to immunisation by 2030. The plan aims for at least 90% vaccination coverage across the nation, ensuring no subnational region drops below 80% for all routine vaccines by 2030(Wasswa et al., 2025). Similarly, the Immunisation Agenda 2030 seeks to provide complete immunisation for every child, no matter their location, age, socioeconomic background, or gender-related challenges(Wasswa et al., 2025).

Despite notable progress in vaccination efforts, a significant number of children, particularly in sub-Saharan Africa, remain unvaccinated or under-vaccinated (Wasswa et al., 2025). Immunisation programmes, such as supplementary immunisation activities, aim to design strategies to effectively cover all age cohorts and reduce the number of unimmunised individuals. The following section addresses supplementary immunisation activities.

2.3.3. Immunisation Campaign

Vaccination campaigns serve as a strategy to administer vaccines to large groups of children or individuals rapidly. These campaigns can be organised at either the national or sub-national level. They may focus on a single antigen or be integrated with other health interventions, depending on the country's specific needs and goals. Various types of vaccination campaigns exist (WHO, 2025a). The following segment discusses the two major immunisation strategies.

2.3.4. Supplementary Immunisation Activities (SIA)

SIAs administer vaccination to all targeted individuals, regardless of their previous vaccination history. The aim is to rapidly enhance herd immunity and reduce the number of susceptibles, progressing towards disease control or elimination (WHO, 2025a). In the African Region, SIA has demonstrated effectiveness in reaching high coverage and assisting communities with limited healthcare infrastructure. Polio supplementary immunisation activity (SIA) is a mass immunisation campaign designed to supplement routine immunisation and help eradicate polio (Ahmad et al., 2023; Jean Baptiste et al., 2021). It serves as one of the four key pillars of polio eradication within the Global Polio Eradication Initiative (GPEI), alongside routine immunisation, active wild poliovirus surveillance, and targeted mop-up campaigns (Ahmad et al., 2023; Jiee et al., 2021).

SIA is generally carried out by international agencies like the World Health Organisation (WHO) and UNICEF, with support from local governments. It takes place at the national level during National Immunisation Days (NIDs) (WHO. & PAHO., 2016). In areas with high-risk polio transmission, SIAs happen during sub-national immunisation days (SNIDs), follow-up rounds

after outbreaks, or through outreach efforts and door-to-door campaigns, especially in regions with low routine immunisation coverage (WHO. & PAHO., 2016). The primary goal of SIA activities is to boost vaccine coverage by giving two doses of oral polio vaccine, spaced 4–6 weeks apart, to all children under five, regardless of their previous immunisation status (WHO. & PAHO., 2016).

These activities help improve access to vaccination for marginalised groups and address barriers related to vaccination-seeking behaviour and awareness, particularly in poor and hard-to-reach populations (Ahmad et al., 2023; Voorman et al., 2024). These campaigns are necessary due to the inability of the Fixed Post routine immunisation strategies to reach all eligible children. Therefore, we discuss Routine immunisation in the next section.

2.3.5. Routine Immunisation

Routine immunisation programs are structured to provide essential vaccination services to children from birth up to 11 months. These programs follow a carefully planned schedule to ensure that children receive necessary vaccines at optimal times for effective immunity development (Sato & Titus, 2021). At the time of birth, newborns are typically administered initial doses of vaccines such as hepatitis B.

Following this, children receive additional doses at subsequent intervals: at 4 weeks, 10 weeks, and 14 weeks of age. As they grow, further vaccinations are scheduled at 6 months, 9 months, and 12 months old, culminating around the 15-month mark (Omoleke et al., 2023). These vaccinations help protect against various preventable diseases, including diphtheria, tetanus, pertussis, polio, and others.

In addition to the routine immunisation schedule for infants, the HPV (Human Papillomavirus) vaccine is targeted at an older age cohort, specifically children and adolescents aged 9 to 13 years. Administration of the HPV vaccine begins at age 9. It continues through age 13, typically given in multiple doses to ensure adequate protection against HPV-related diseases, including cervical cancer, other cancers, and genital warts (Omoleke et al., 2023). Details and specific protocols related to the HPV vaccination schedule can be found in Annexure 3, which provides further guidance on dosage, frequency, and administration procedures.

Barriers that lead to missed opportunities for vaccination include several critical issues, such as poor data quality, which hampers accurate tracking and planning; deficiencies in microplanning that affect the efficient deployment of vaccination campaigns; and an insufficient number of healthcare workers, which limits outreach and service provision. These obstacles collectively impede achieving optimal vaccination coverage, thus raising the number of zero-dose and under-immunised individuals in many communities. Addressing this is essential for improving immunisation outcomes. The following section addresses the unimmunised and under-immunisation.

2.4. Under-Immunised and Zero-dose in Nigeria

The Reach Every District (RED) strategy, part of the Expanded Programme on Immunisation (EPI), focuses on ensuring that every child and pregnant woman has equitable access to vaccines and care (Kanyuuru et al., 2015; Oot et al., 2023). Unfortunately, ongoing challenges have led to an increasing number of zero-dose and under-immunised children, jeopardising herd immunity and opening the door for outbreaks of vaccine-preventable diseases

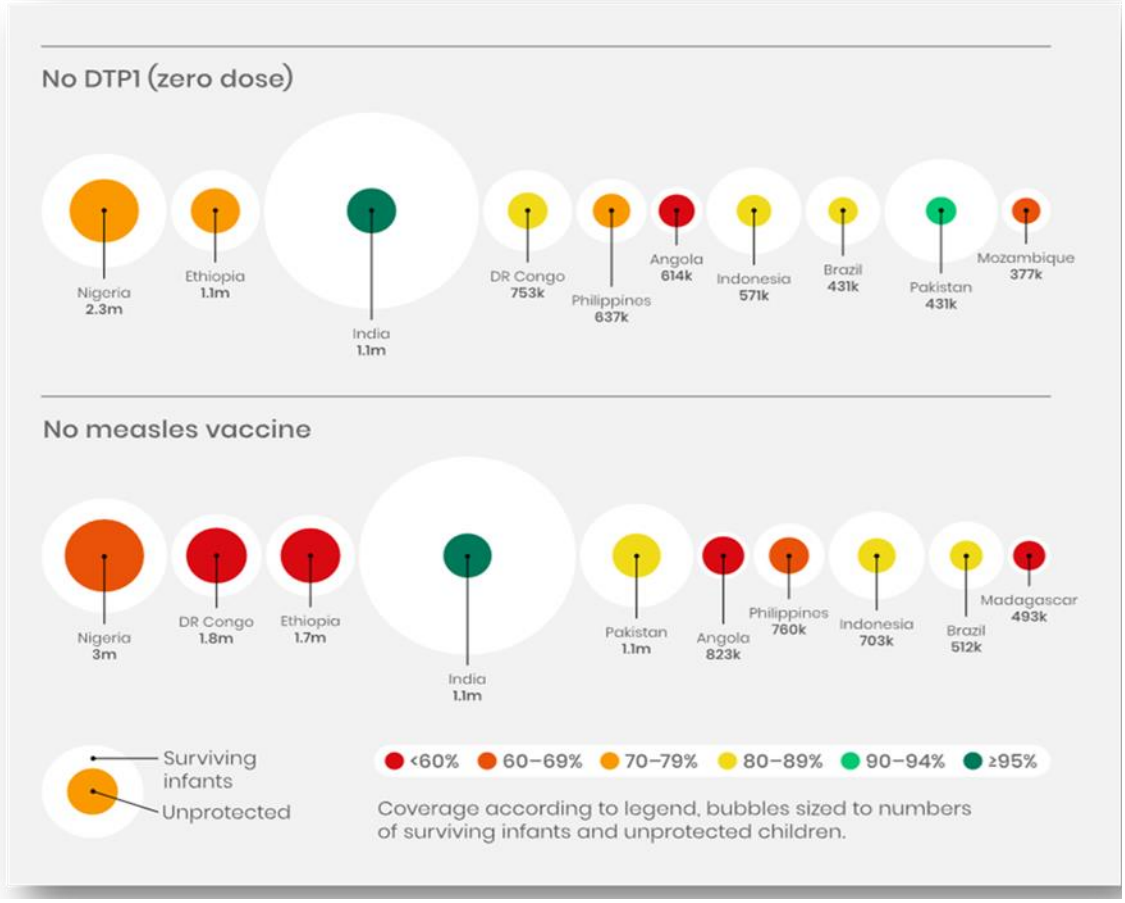
(VPDs) (Adesola et al., 2023; Aheto et al., 2023; GAVI, 2022). Worldwide, the number of zero-dose children climbed nearly 40%, rising from 13.3 million in 2019 to 18.2 million in 2021, primarily due to the COVID-19 pandemic (Basu et al., 2023; Dadari et al., 2023; GAVI, 2022).

Ten African countries account for 58% of children without measles or pentavalent vaccines (WHO & UNICEF, 2022). Another research conducted in DRC says, in 2022, there were an estimated 14.3 million unvaccinated children (zero-dose children), with an additional 6.2 million partially vaccinated, the majority of whom reside in sub-Saharan Africa (Ishoso et al., 2023).

In Nigeria, out of approximately 8.7 million children under one year, 2.3 million are considered zero-dose children, making Nigeria the leading country in the global zero-dose child crisis (GAVI, 2023; Ishoso et al., 2023; Wigley et al., 2022). Conflict, displacement, inaccessible areas, nomadic lifestyles, rapid urbanisation, and severe shortcomings in health service delivery and workforce capacity exacerbate this trend in many LMIC, including Nigeria (Idris et al., 2022).

The introduction of the zero-dose immunisation programme by GAVI and the catch-up vaccination highlight the suboptimal performance of immunisation services in many countries (WHO et al., 2023). According to the WUENIC data presented in the diagram below, a total of 10 countries are responsible for a significant 58% of zero-dose children worldwide. This indicates that a concentrated effort in these countries could substantially impact global vaccination coverage, highlighting the importance of targeted interventions and resource allocation in these regions, as illustrated in Figure 1.

Figure 1 – Immunisation Coverage Data showing zero-dose by Antigen



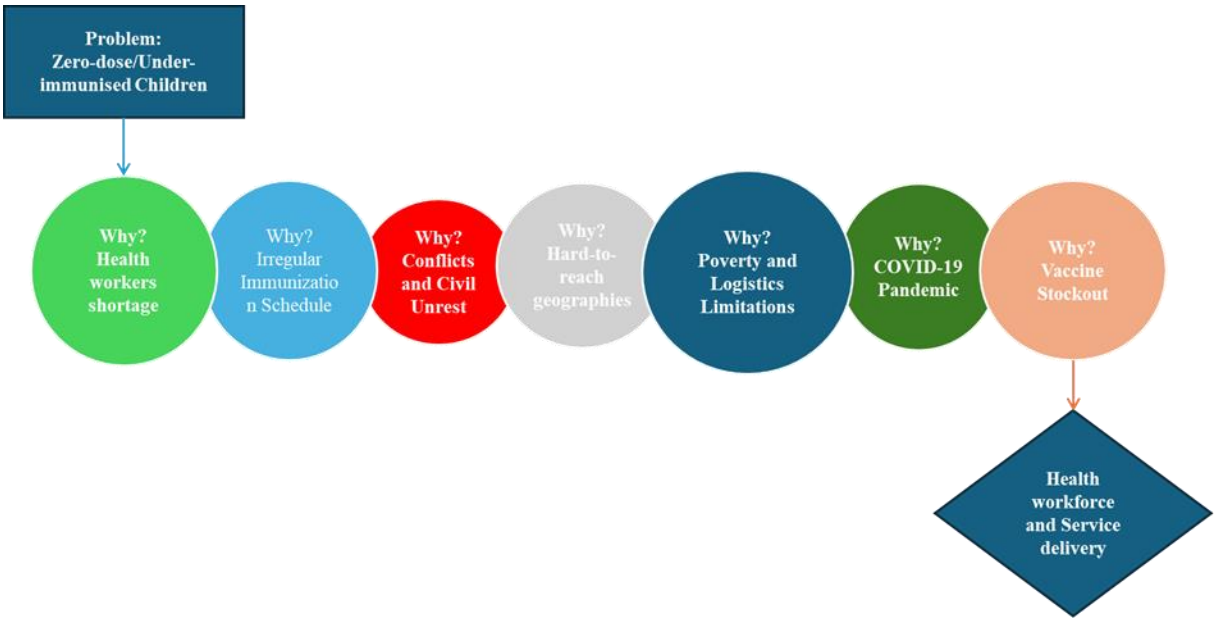
Globally, among the top 10 countries for DTP zero-dose children in 2022, Mozambique has replaced Myanmar, which was part of this group in 2021(WHO/UNICEF, 2019). In the MCV zero-dose group, Madagascar replaced Tanzania in 2022 compared to 2021. Nigeria accounts for 26.5% of the global burden of zero-dose children due to suboptimal health service delivery, workforce shortages, conflict, infrastructure limitations, vaccine stockouts at health centres, poverty, and factors related to vaccine hesitancy (WHO/UNICEF, 2019). Data triangulation has identified over 200 local government areas in 37 states as contributors to the country's high number

of zero-dose children, as seen in annexure 2, according to geopolitical zones. This includes administrative data and input from multiple interventions. Utilising the WHO six building blocks framework, a root cause analysis was carried out using the five whys by mapping data from reactive vaccinations during VPD outbreaks, Polio Supplementary Immunisation Activities, and Routine Immunisation Intensification, as depicted in the diagram below.

The shortage of health workers and heavy workloads have led to weekly vaccination sessions at many rural primary healthcare centres, increasing missed vaccinations. Parents in nearby communities struggle to reach health centres up to 5 kilometres away due to poverty and poor road access. Insecurity further complicates access, rendering some areas wholly or partially unreachable(Basu et al., 2023). Health workers face challenges in outreach immunisation, even with armed support, due to threats of kidnapping or violence. Parents who attend often find vaccines out of stock and may not return due to financial constraints. In Bauchi, Nigeria, research assessed a direct delivery program to ensure vaccine availability and reduce stockouts at health facilities(Sabahelzain et al., 2025).

A catch-up vaccination strategy, under the WHO integrated service delivery model, effectively targets the root causes of this problem(Sato, 2023). This strategy involves immunising individuals who, due to various factors such as delays, stockouts, access issues, hesitancy, or service interruptions, have not received the vaccines they are eligible for under the national immunisation program schedule, as seen in annexe 3. The following section discusses policy implications and strategies to reach zero-dose children in Nigeria (London, 2025).

Figure 2 - Root cause Analysis for Sub-optimal vaccine coverage performance



The shortage of health workers and heavy workloads have led to weekly vaccination sessions at many rural primary healthcare centres, increasing missed vaccinations. This has also been made worse due to the migration of healthcare workers to high-income countries seeking better payment, which in turn has affected the immunisation data quality and coverage. Parents living in nearby communities struggle to reach settlements and find it challenging to reach health centres up to 5 kilometres away due to poverty and poor road access. Insecurity further complicates access, rendering some areas wholly or partially unreachable (Gulumbe et al., 2024). Health workers face challenges in outreach immunisation, even with armed support, due to threats of kidnapping or violence. Parents who attend often find vaccines out of stock and may not return due to financial constraints. In Bauchi, Nigeria, research assessed a direct delivery program to ensure vaccine availability and reduce stockouts at health facilities (Sato et al., 2021).

A catch-up vaccination strategy, under the WHO integrated service delivery model, effectively targets the root causes of this problem(WHO, 2021a). This strategy involves immunising individuals who, due to various factors such as delays, stockouts, access issues, hesitancy, or service interruptions, have not received the vaccines they are eligible for under the national immunisation program schedule, as seen in annexe 3. Children who are under-immunised or unvaccinated continue to be a significant challenge in accurately assessing immunisation coverage through administrative data. This is because such data often fail to account for children who have not received all the necessary vaccines, leading to an underestimation of the true coverage rates. The presence of unvaccinated children skews the data, making it unreliable as a standalone measure for evaluating the effectiveness of immunisation programmes. Consequently, relying solely on administrative data can result in missed opportunities for targeted interventions and policy adjustments aimed at increasing vaccine coverage and ensuring herd immunity. The adjoining section discusses immunisation data.

2.5. Routine Immunisation Data

Routine immunisation data is essential for shaping global and national health policies. It provides critical information on vaccination coverage, identifies service delivery gaps, and aids targeted efforts to prevent vaccine-preventable disease outbreaks. Collected systematically through health systems, this data is vital for monitoring progress towards immunisation goals, including those established by the World Health Organisation's (WHO) Immunisation Agenda 2030 (GPEI, 2023; IA2030, 2024).

2.5.1. Sources and Collection Methods

Routine immunisation data is typically gathered through three main channels:

I. Administrative Data: This includes records from health facilities on the number of vaccines administered, often reported monthly or quarterly. While useful for real-time monitoring, it may be subject to inaccuracies due to reporting errors or outdated population estimates (Ogbuabor et al., 2022).

II. Survey Data: Population-based surveys, such as Demographic and Health Surveys (DHS) or Multiple Indicator Cluster Surveys (MICS), provide more reliable estimates by verifying vaccination status through health cards or caregiver recall (WHO & UNICEF, 2021).

III. Official Estimates: WHO and UNICEF synthesise administrative and survey data, along with expert assessments, to produce annual country-level immunisation coverage estimates. These are considered the most robust indicators of national performance (WHO & UNICEF, 2023).

2.5.2. Global and National Dashboards

The WHO Immunisation Data Portal provides a detailed and comprehensive overview of global immunisation trends. It includes key coverage rates for essential vaccines such as DTP (diphtheria, tetanus, and pertussis), measles, polio, and other vaccinations, offering valuable insights into the progress and challenges faced worldwide. Additionally, the portal tracks disease incidence rates, which help countries evaluate the effectiveness and impact of their immunisation programs over time (WHO, 2025b).

Over 60,000 healthcare workers were trained, and each local government area (LGA) received tools to support data entry and analysis. This system has helped identify underperforming regions and guide corrective actions (Shuaib et al., 2020).

2.5.3. Impact and Challenges

Accurate routine immunisation data enables governments and health partners to:

- Detect coverage gaps and prioritise underserved populations
- Allocate resources efficiently
- Evaluate the effectiveness of immunisation campaigns
- Respond swiftly to disease outbreaks

However, significant challenges continue to impede progress in immunisation data management. The quality of data collected can often be compromised due to incomplete reporting, which may result from inconsistent recording practices or a lack of standardised procedures. Additionally, many regions suffer from inadequate digital infrastructure, such as limited access to reliable internet and modern data management systems, hindering real-time data collection and analysis. The capacity of health workers to accurately gather and report data is also limited, often due to insufficient training, workload burdens, and resource constraints. In low-income countries in particular, discrepancies frequently emerge between administrative records and survey-based data, underscoring the urgent need for robust data validation mechanisms, improved coordination, and better integration of various data sources.

Strengthening routine immunisation data systems is critical to monitor progress and identify gaps accurately, ultimately supporting efforts to achieve universal vaccine coverage. To address these issues comprehensively, investments must be made in advanced digital tools tailored to local contexts, ongoing workforce training to enhance skills and data literacy, and active community engagement to promote trust and participation. Together, these measures can significantly improve the accuracy, reliability, and utility of immunisation data, driving more effective and equitable immunisation programs (WHO, 2025b). As countries strive to recover from disruptions caused by the COVID-19 pandemic, robust immunisation data will be key to rebuilding resilient health systems.

2.6. AFP Surveillance

Acute Flaccid Paralysis (AFP) surveillance is a critical component of the Global Polio Eradication Initiative (GPEI), serving as its most sensitive and effective method for the early detection and monitoring of poliovirus transmission worldwide (GPEI, 2025; Jil et al., 2022). This comprehensive, case-based disease surveillance system focuses explicitly on identifying instances of sudden onset weakness or paralysis in children under the age of 15, regardless of the suspected cause, which allows for a broad approach to disease detection (Watkins et al., 2009). By meticulously tracking these cases, AFP surveillance ensures that even the rarest or silent cases of poliomyelitis, those that may not present obvious symptoms but still pose a risk of spreading, are promptly identified, thoroughly investigated, and swiftly addressed through public health interventions.

As the global community progresses towards the ambitious goal of complete polio eradication, AFP surveillance remains an indispensable tool (GPEI, 2025). It not only confirms the absence of wild poliovirus (WPV) but also plays a vital role in detecting vaccine-derived poliovirus (VDPV), which can emerge in under-immunised populations, and other neurological conditions that may mimic poliomyelitis (Abbott et al., 2021; Abdel-Fattah et al., 2019; Alleman et al., 2023; Verani & Laender, 2020). This rigorous surveillance system supports timely response actions, helps evaluate vaccination efforts, and ultimately contributes to the certification of a polio-free world.

Globally, Acute Flaccid Paralysis (AFP) surveillance is a comprehensive system implemented in over 190 countries around the world. It is supported by the World Health Organisation (WHO) and key partners of the Global Polio Eradication Initiative (GPEI), which include organisations such as UNICEF, the Centres for Disease Control and Prevention (CDC), Rotary International, and the Bill & Melinda Gates Foundation (GPEI, 2025). This surveillance system involves several critical components and processes designed to detect, monitor, and respond to cases of AFP, primarily to ensure the eradication of poliovirus and to maintain high levels of public health security across different nations.:

- Routine case detection in health facilities
- Active surveillance through regular visits to hospitals and clinics
- Community-based surveillance (CBS), which engages local informants to report suspected cases
- Environmental surveillance, which tests sewage samples for poliovirus

The Global Polio Laboratory Network (GPLN) is a comprehensive international network consisting of numerous diagnostic laboratories that have achieved accreditation, with 146 WHO-certified labs spread across 92 countries worldwide (GPEI, 2025). These laboratories collectively process more than 220,000 stool samples each year, which are crucial for the surveillance and control of poliovirus.

Their responsibilities include accurately identifying different strains of the poliovirus, performing advanced genomic sequencing to analyze genetic variations, and monitoring the pathways through which the virus transmits within populations (GPEI, 2025). This extensive network plays an essential role in global efforts to eradicate polio by providing critical data for outbreak response, vaccine efficacy assessments, and understanding the epidemiological landscape of poliovirus circulation (GPEI, 2025).

2.6.1. Surveillance Performance Indicators

To ensure the effectiveness and reliability of Acute Flaccid Paralysis (AFP) surveillance systems, the World Health Organisation (WHO) has established a comprehensive set of key performance indicators (KPIs). These KPIs serve as critical metrics designed to evaluate various facets of the surveillance system, including its sensitivity (the ability to detect actual cases), timeliness (the speed at which cases are identified and reported), and completeness (the extent to which all cases are captured and recorded) (GPEI, 2025). These indicators are systematically monitored and analysed, as detailed in Table 1, to facilitate continuous improvement, ensure prompt response to potential outbreaks, and ultimately support the global goal of poliovirus eradication.

Table 1: Surveillance Performance Indicators

Indicator	Target Standard	Purpose
Non-polio AFP rate	≥3 per 100,000 children <15 years	Measures the sensitivity of surveillance
Stool adequacy	≥80% of AFP cases with two stool samples collected within 14 days of onset	Ensures timely and proper specimen collection
Timeliness of reporting	≥80% of expected reports submitted on time	Tracks the responsiveness of the system
60-day follow-up	≥80% of AFP cases followed up for residual paralysis	Confirms diagnosis and outcome
Lab turnaround time	Specimens processed within 28 days	Ensures timely lab confirmation

2.6.2. Case-Based Disease Surveillance

AFP surveillance is a classic example of case-based disease surveillance, where each suspected case is individually investigated. This includes, according to GPEI:

- Case notification: Immediate reporting of suspected AFP cases
- Case investigation: Detailed clinical history, physical examination, and contact tracing
- Specimen collection: Two stool samples collected 24 hours apart
- Laboratory testing: Identification of poliovirus or other enteroviruses
- Final classification: Determination of whether the case is polio, non-polio AFP, or polio-compatible

Case-based surveillance is a comprehensive approach that enables detailed analysis of disease patterns at a granular level (Bawa et al., 2019). Collecting data from individual cases allows public health officials to identify high-risk areas with greater precision, thereby facilitating the

implementation of targeted immunisation campaigns focused on populations most in need. Additionally, this surveillance method supports an integrated approach to disease monitoring by linking data from Acute Flaccid Paralysis (AFP) cases with information on other notifiable diseases, such as measles, yellow fever, and meningitis (Alegana et al., 2024). This interconnected system enhances the overall ability to detect, track, and respond to multiple infectious diseases efficiently, improving public health outcomes.

Africa has achieved significant progress in acute flaccid paralysis (AFP) surveillance, marking a pivotal milestone in the continent's public health efforts. In August 2020, Africa was officially declared free of wild poliovirus, a feat made possible through comprehensive and sustained surveillance systems, community engagement, and extensive immunisation campaigns that targeted vulnerable populations. Despite these advances, the region continues to face unique challenges, particularly concerning the detection and control of circulating vaccine-derived poliovirus (cVDPV), which poses ongoing risks to poliovirus eradication efforts (Abbott et al., 2021; Alleman et al., 2023). A recent detailed analysis focusing on AFP surveillance across 19 countries in East and Southern Africa has shed light on the improvements achieved over the period from 2022 to 2023. The data indicate that the non-polio AFP detection rate has increased from 4.4 to 4.7 per 100,000 children under 15 years old, reflecting enhanced sensitivity of surveillance activities (Lukwago et al., 2013; Mustafa et al., 2025; Rosewell et al., 2012; Wells et al., 2022).

Additionally, the rate of timely investigations of AFP cases has improved from 89% to 91%, demonstrating greater promptness in case response (Ohta et al., 2007). However, despite these positive trends, certain operational disparities remain. Specifically, issues related to the transportation of samples from case sites to laboratories and delays in laboratory turnaround times continue to hinder swift case confirmation and response. These logistical challenges underscore

the urgent need for infrastructural improvements, better supply chain management, and capacity building within laboratories to ensure more rapid and accurate diagnosis. Addressing these remaining gaps is crucial for maintaining and further strengthening the continent's polio surveillance and eradication efforts.

Community-based surveillance has become a vital tool in Africa. In Ethiopia, Kenya, and Nigeria, CBS has enhanced early detection and reporting of AFP cases, especially in remote and underserved areas (Biru et al., 2025). Mobile apps, awareness campaigns, and training of community informants have bolstered surveillance networks. Nigeria's progress from polio-endemic to polio-free status demonstrates the strength of AFP surveillance (Shuaib et al., 2018; Wells et al., 2022). The country was certified free of WPV in 2020 but still faces outbreaks of cVDPV due to low immunisation coverage in certain regions.

Nigeria's AFP surveillance system is among the most sensitive in Africa. In Sokoto State, for example, the non-polio AFP rate ranged from 9.1 to 23.5 per 100,000 children under 15 between 2012 and 2019, greatly exceeding WHO standards. Stool adequacy rates consistently stayed above 92%, and timely specimen transport remained above 80% (Abbott et al., 2021).

Innovative strategies have bolstered Nigeria's surveillance:

- SMS reminders to health workers improved reporting and specimen collection
- Peer reviews and validation visits identified gaps in data quality and led to corrective actions
- Integration with other disease surveillance systems enhanced efficiency and resource use

Despite these notable successes, several challenges persist that need to be addressed to improve health surveillance systems further. A peer review conducted across 16 high-performing states revealed significant discrepancies between the number of Acute Flaccid Paralysis (AFP) cases reported and those validated through rigorous verification processes. The concordance rates, which measure agreement between reported and validated cases, varied widely from as low as 58% to a perfect 100%, indicating inconsistencies in reporting accuracy (Ali et al., 2023; Amodan et al., 2022; Bessing et al., 2023).

Furthermore, the misclassification of cases due to conditions with similar clinical presentations, such as spastic paralysis caused by other neurological conditions and illnesses like malaria, poses additional difficulties in accurate diagnosis and reporting. This highlights the critical need for ongoing training programs for healthcare workers and continuous supervision to maintain high reporting standards. To sustain and strengthen these surveillance efforts, global partners must continue to provide robust support through capacity-building initiatives, technical assistance, and sustained funding. These measures are vital to ensuring that surveillance systems remain strong (WHO, 2021a), accurate, and responsive to emerging health threats, ultimately safeguarding public health effectively.

2.7. Theoretical Framework

The most suitable overarching theoretical framework here is a Health Systems Performance and Evaluation Framework, based on the WHO Health System Building Blocks (service delivery, health workforce, information, financing, governance, and medicines/vaccines) (Doshmangir et al., 2025; WHO, 2021a). This framework is combined with Donabedian's Model of Healthcare

Quality (structure, process, outcome) and is supported by Epidemiological Surveillance Theory (Alkorashy & Al-Hothaly, 2022; Tefera et al., 2021; Tossaint-Schoenmakers et al., 2021). Together, these concepts provide a structured way to understand how surveillance data, immunisation service delivery, and health outcomes interconnect through predictive modelling, thereby informing public health policy and practice.

1. WHO Health System Building Blocks

The WHO framework highlights six key areas for effective health systems: service delivery, health workforce, information systems, medical products/vaccines, financing, and leadership/governance (Doshmangir et al., 2025). In immunisation, AFP surveillance is a crucial part of the information system, collecting data on polio outcomes that indirectly indicate vaccination coverage. Additionally, the NICS survey assesses service delivery results, offering population-level insights into immunisation rates. Combining these datasets through statistical modelling helps bridge a significant challenge in health systems: the disconnect between routine surveillance data and independently verified population coverage estimates.

2. Donabedian's Model (Structure–Process–Outcome) (Tossaint-Schoenmakers et al., 2021)

Donabedian's framework provides a complementary lens to assess quality in health service delivery. This includes.

- Structure includes the availability of AFP surveillance infrastructure, reporting mechanisms, and survey design methodology.

- Process encompasses the conduct of surveillance activities, vaccine administration, and survey data collection.
- Outcomes refer to immunisation coverage as measured by NICS, which serves as a benchmark for evaluating health system performance.

By analysing AFP coverage data (process) alongside NICS survey results (outcomes), the thesis places immunisation performance within an evaluative framework that considers both service delivery and overall population effectiveness.

3. Surveillance and Evaluation Theory

Epidemiological surveillance theory highlights that surveillance data should do more than just track disease trends; it should also inform actionable decisions (Jaramillo et al., 2022). Although AFP surveillance is mainly aimed at detecting polio, it also helps assess immunisation performance. This thesis uses mixed-effects modelling to implement data triangulation, combining multiple sources to enhance accuracy and reliability. This approach aligns with evaluation theory's focus on the validity, generalisability, and usefulness of data for guiding interventions.

4. Predictive Modelling as a Theoretical Extension

Statistical modelling techniques, such as linear regression and mixed-effects models, expand the theoretical framework by linking health system inputs like AFP coverage to health system outcomes like NICS coverage. Predictive modelling exemplifies health system learning, allowing data-driven insights to inform program design, improve surveillance, and support real-time decision-making (Hoffman & Walters, 2022).

This integrated framework is ideal for the thesis because it offers a comprehensive perspective that connects health systems theory, service quality assessment, and surveillance science. It recognises that immunisation coverage is both a health outcome and a broader system performance indicator (Hoffman & Walters, 2022). Using this framework, the thesis enhances both theoretical insights and practical applications of how surveillance data can be utilised for accurate, real-time monitoring of immunisation coverage and intervention effects. The following chapter discusses the methods and methodology of this research.

CHAPTER THREE: DATA AND METHODOLOGY

3.1. Introduction

As outlined in Chapter One, the main aim of this study is to thoroughly assess and develop detailed models to understand the progress of routine immunisation programmes across Nigeria. The focus is on analysing the effectiveness, coverage, and challenges faced by these programmes to enhance public health outcomes. The evaluation will rely on comprehensive data collected from the 2022 Acute Flaccid Paralysis (AFP) case-based surveillance system, which offers vital insights into polio and other vaccine-preventable diseases. Additionally, data from the Nigeria Immunisation Coverage Survey (NICS) will be utilised to evaluate vaccine coverage levels across various regions and populations within the country.

This chapter elaborates on the systematic steps involved in the data collection process, including the methodologies used to gather accurate and reliable data from various sources. It also details the procedures for data analysis, emphasising how the study population has been defined and included.

The chapter aims to provide a clear understanding of the processes and methods employed to ensure the robustness and validity of the study findings, ultimately contributing to strategies for improving immunisation coverage and disease surveillance in Nigeria. In the following section, the study will thoroughly describe the research design, outlining the methodology, data collection techniques, sampling methods, and analytical strategies employed to ensure the validity and reliability of the research findings.

3.2. Research Design

We conducted a gap analysis of routine immunisation data for five different cohorts, utilising a descriptive cross-sectional design to evaluate secondary data from a population at a specific point in time. This analysis drew on 2022 Nigeria AFP case-based surveillance data (Levin, 2006; Mellis, 2020). Such analyses are commonly employed to assess health outcome prevalence, comprehend health determinants, and characterise population features (Savitz & Wellenius, 2023; Wang & Cheng, 2020).

3.3. Population of the Study

A total of 7613 samples out of 10491 from Nigeria's 2022 AFP case-based surveillance data were classified into five cohorts for children using routine immunisation OPV data and mapping as proxies from 2018 to 2022 to understand the transmission dynamics of poliovirus from regions with coverage gaps.

- Children aged 4 - 11 months were considered the 2022 cohort (n = 549)
- Children aged 12 – 23 months were considered the 2021 cohort (n = 2312)
- Children aged 24 – 35 months were considered the 2020 cohort (n = 2338)
- Children aged 36 – 47 months were considered as the 2019 cohort (n = 1459)
- Children aged 48 – 59 months were considered the 2018 cohort (n = 955).

Therefore, the doses of OPV received for routine immunisation by the cohort of children older than 12 months are categorised into four groups for the following gap analysis.

- >=3 OPV doses: Fully immunised

- 1 – 2 OPV doses: Partially immunised
- 0 dose: No dose
- Unknown OPV vaccination history

  We tried to analyse age-matched coverage for children <12 months (2022 cohort).

- < 6 weeks (<1.5 months): No RI dose
- 6 to <10 weeks: 1 dose/RI-OPV1 dose
- 10 to <14 weeks: 2 doses/OPV1 and OPV2 doses
- 14 to <47 weeks: 3 doses/OPV1, OPV2, and OPV3

For this study, we considered children above four months of age to be the minimum age to be eligible for 3 doses of OPV (i.e. OPV1, OPV2, and OPV3). The cohort, which was meticulously categorised according to specific parameters, was subsequently analysed in conjunction with the findings from the 2021 National Immunisation Survey (WHO & UNICEF, 2021) which assessed the 2020 data for 12 35–to 35–month–old children. This survey encompassed data collected from 37 states in Nigeria that actively participated in the Multiple Indicator Cluster Surveys (MICS) or the National Immunisation Coverage Surveys (NICS).

3.4. Methods of Data Analysis

A comprehensive comparative gap analysis utilizing mixed-methods approaches was conducted to evaluate and contrast the different data sources, specifically focusing on the 2022 Nigeria AFP (Acute Flaccid Paralysis) data and the 2021 MICS (Multiple Indicator Cluster

Survey)/NICS (National Immunization Coverage Survey) report data, with particular emphasis on assessing the coverage of Oral Polio Vaccine (OPV). This analysis aimed to identify discrepancies, complementarities, and reliability issues between the surveillance and survey data sources to inform policy and programmatic decisions (WHO & UNICEF, 2021, 2023), using R programming.

Gap Analysis Context, R programming

The researchers established a condition that effectively tracks gaps and identifies poliovirus reservoirs using the 2021 MICS/NICS survey data parameters, compared with the 2022 AFP data for RI. **Code:**

```
library(dplyr)
df <- data.frame(gap = c(5, 12, 25, 35))
df <- df %>%
mutate (gap_category = case_when(gap <= 10 ~ "<=10% gap", gap > 10 & gap <= 20 ~ "11 - 20% Gap",
gap > 20 & gap <= 30 ~ "21 - 30% Gap", gap > 30 ~ ">30% Gap"))
```

The gap (OPV3_Cov_AFP - OPV3_Cov_NICS) for states in Nigeria and the observations for the RI/OPV dose gaps are computed as continuous variables. Therefore, four conditions for gaps were identified for this analysis.

Explanation:

1. Gap <= 10 ~ "<=10% gap"
   - Identifies States or observations where the gap is 10% or less.
   - Implies relatively good vaccination coverage.
2. Gap > 10 & Gap <= 20 ~ "11 - 20% Gap"
   - Represents moderate coverage gaps, needing improvement.
3. Gap > 20 & Gap <= 30 ~ "21 - 30% Gap"
   - Highlights significant missed opportunities, often requiring targeted interventions.
4. Gap > 30 ~ ">30% Gap"
   - Indicates critical gaps, suggesting urgent action is needed (e.g., intensified campaigns, outreach, supervision).
5. is.na (Gap) ~ "Data Missing" (optional)
   - Catches and labels missing values, which helps during reporting or data cleaning.

Also, a simple nested IF conditional analysis was conducted on Excel to compare the gap outcomes for easy replication purposes.

Gap Analysis Context Excel

The researchers established a condition that effectively tracks gaps and identifies poliovirus reservoirs using the 2021 MICS/NICS survey data parameters, compared with the 2022 AFP data for RI.

Where:

Gap (OPV3_Cov_AFP – OPV3_Cov_NICS) for states in Nigeria.

Therefore, four conditions for gaps were identified for this analysis.

Explanation:

1. IF(Gap<=10,"<=10% gap",...)

- This checks if the value in Gap is 10 or less.
- If true, it returns "<=10% gap".
- If false, it moves on to the next IF condition.

2. IF (Gap<=20, "11 - 20% Gap",...)

- Now it checks if the value is 20 or less (but more than 10).
- If true, it returns "11 - 20% Gap".
- If false, it continues to the next condition.

3. IF (Gap<=30, "21 - 30% Gap",...)

- This checks if the value is 30 or less (but more than 20).
- If true, it returns "21 - 30% Gap".
- It returns the final option if false (i.e., more than 30).

A Pearson product–moment correlation assessed the relationship between AFP suspected cases and zero-dose counts across the age group. The study also explored non-linear patterns by using a Spearman correlation, considering that the data might not follow a normal distribution. This approach aligned the burden of zero-dose with the AFP suspected case count based on the collected data. Additionally, machine learning models were employed to predict outbreak probabilities in these regions, while a logistic regression presented as a forest plot helped identify hotspots for AFP cases at the state and LGA levels.

Using the XGBoost model, the analysis also forecasted the zero-dose count and actual figures based on the AFP OPV zero-dose count by LGA. A Time-Series Coverage Analysis employing difference-in-difference with anchoring was conducted to adjust the true coverage of routine immunisation downloaded from DHIS2 for 2022–2024. The analysis aligned 2024 immunisation coverage with interventions or activities carried out at the sub-national level to evaluate the impact of interventions before and after across states and LGAs. To forecast the 2025 coverage, the study utilises the ARIMA model, using 2022-2024 data to estimate the coverage in R programming.

3.5. Ethical Consideration

Research using immunisation coverage and surveillance data involves important ethical issues, mainly because it handles sensitive health information, vulnerable groups, and results that impact public health policies. The moral aspects of this thesis can be categorised into five main areas: maintaining data integrity and confidentiality, ensuring informed consent and proper data use, promoting equity and justice, upholding beneficence and non-maleficence, and ensuring accountability in sharing findings.

1. Data Integrity and Confidentiality

The thesis utilises secondary datasets like the Nigeria Immunisation Coverage Survey (NICS) and Acute Flaccid Paralysis (AFP) surveillance data. While the data are anonymised and aggregated, it is ethically crucial to uphold confidentiality and prevent the inadvertent identification of individuals or small communities through data linkage or modelling. Implementing data security measures, such as encrypted storage and compliance with institutional data protection policies, is essential for protecting sensitive information. Researchers also have an ethical obligation to avoid manipulating, misrepresenting, or selectively reporting data to support specific outcomes.

2. Informed Consent and Data Use

Although this study uses secondary data, the concept of informed consent still applies. Participants in surveys like NICS usually agree to their data being utilised for research and policy review. The researcher must verify that data use stays within the bounds of the initial consent. Additionally, obtaining approval from an institutional review board (IRB) or ethics committee is vital to ensure that data usage complies with national and international research ethics standards.

3. Equity and Justice

Ethical research must adhere to the principle of justice by ensuring that the benefits and burdens are fairly distributed. Immunisation programs frequently focus on vulnerable groups like children, rural residents, and those with limited resources. This research explores how surveillance data can forecast immunisation coverage, helping to identify inequities in vaccine access. Interpreting results to emphasise disparities is ethically crucial, as it guides targeted interventions to underserved populations instead of perpetuating systemic inequalities.

4. Beneficence and non-maleficence

The principle of beneficence mandates that research should have a positive impact on society, while non-maleficence emphasises the importance of avoiding harm. This study's modelling approach aims to enhance monitoring and planning for immunisation services, thereby strengthening the health system. Nonetheless, ethical vigilance is essential to prevent misinterpretation of the results. For instance, if predictive models are shared without highlighting their limitations, policymakers might overdepend on them, resulting in ineffective resource distribution. Transparency about assumptions, data quality, and limitations is vital to ensure that the research benefits public health without unintended harm.

5. Accountability and Dissemination of Findings

Finally, ethical responsibility includes the dissemination of findings. Results should be shared honestly, avoiding exaggeration of predictive accuracy or unsupported claims. Policymakers and stakeholders need practical insights presented within the larger context of the health system. Additionally, the thesis should embrace open knowledge practices by sharing methods and results to allow replication, all while safeguarding data confidentiality. In summary, the ethical considerations in this thesis extend beyond mere institutional compliance; they emphasise respecting human dignity, safeguarding vulnerable groups, and responsibly improving public health. By adhering to principles like confidentiality, justice, beneficence, and accountability, the thesis guarantees that its outcomes are both ethically valid and socially meaningful.

CHAPTER IV: DATA, ANALYSIS AND INTERPRETATION OF FINDINGS

4.1. Introduction

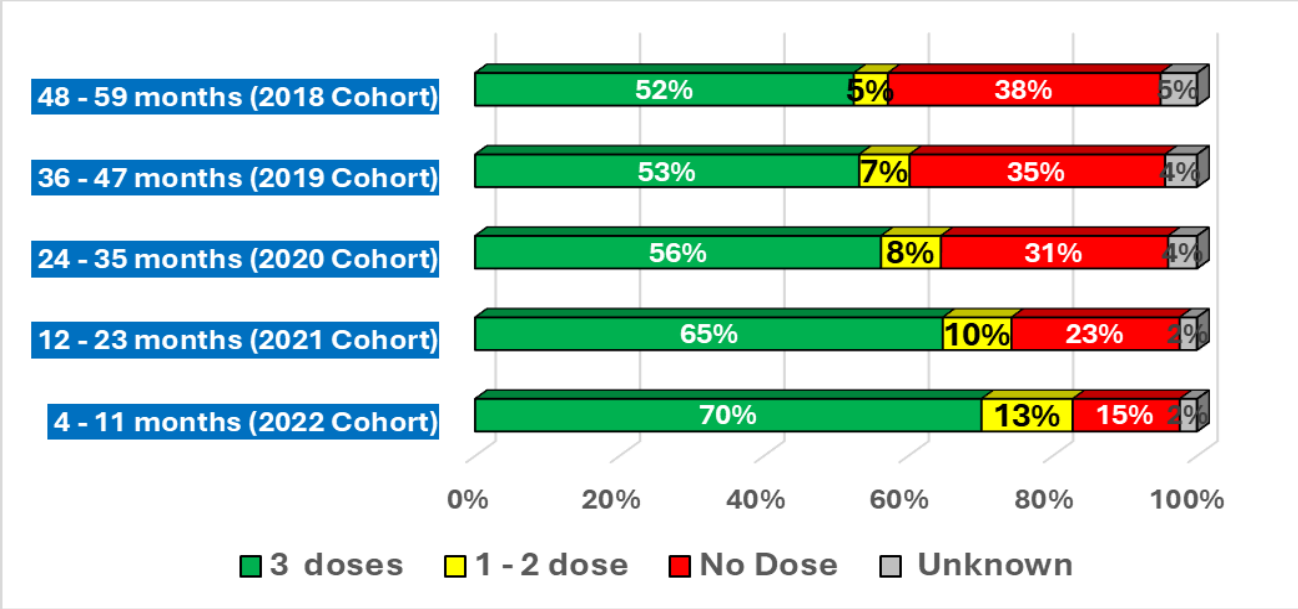
This section presents the mixed-methods findings for this thesis, organised into two distinct phases. In the first phase, the analysis focused on the 2022 AFP cohort data alongside the 2021 NICS data to examine the correlation between AFP data and immunisation coverage, with AFP serving as a validator for accurate immunisation coverage. This analysis aimed to assess the reliability of AFP data as an indicator of immunisation status within the population. In the second phase, additional routine immunisation data were collected from the DHIS2 database covering the years 2022 through 2024. This data was utilised to develop and conduct predictive modelling of infectious disease outbreaks and vaccination interventions, enabling a better understanding of trends and potential future scenarios. The following sections will discuss the detailed findings from both phases, highlighting key insights and implications for immunisation programs and infectious disease control.

4.2. Data Analysis from Routine RI Coverage

Data collected over the last five years reveal a notable increase in the coverage of at least three doses of the Oral Polio Vaccine (OPV) in Nigeria since the establishment of the Nigerian Emergency Routine Immunisation Coordination Centre (NERICC). This trend is illustrated in Figure 1, showing a consistent rise in immunisation rates. The improvement in OPV coverage has been further strengthened by a range of targeted immunisation activities undertaken in the 18 NERICC states. These initiatives encompass zero-dose interventions aimed at vaccinating unvaccinated infants and efforts to intensify routine immunisation (RI). On the contrary, data indicate a decline in zero-dose vaccinations, referring to children who have received no OPV

vaccinations. The proportion of zero-dose children significantly fell from 40% in the 2018 cohort of children aged 48 to 59 months to just 14% among children under 12 months in the 2022 cohort. This decrease underscores the effectiveness of ongoing immunisation efforts while highlighting the challenges in ensuring timely vaccinations for all children with equity.

Figure 3: % >=3 RI/OPV doses improved from 2018 – 2022, (2022 AFP data)



For the 2022 cohort analysis focusing on children under 12 months, children below the age of four months were excluded. This decision was made because it requires at least 14 weeks to complete the 3 OPV doses. Children over 14 weeks or four months can be evaluated for three doses of RI OPV.

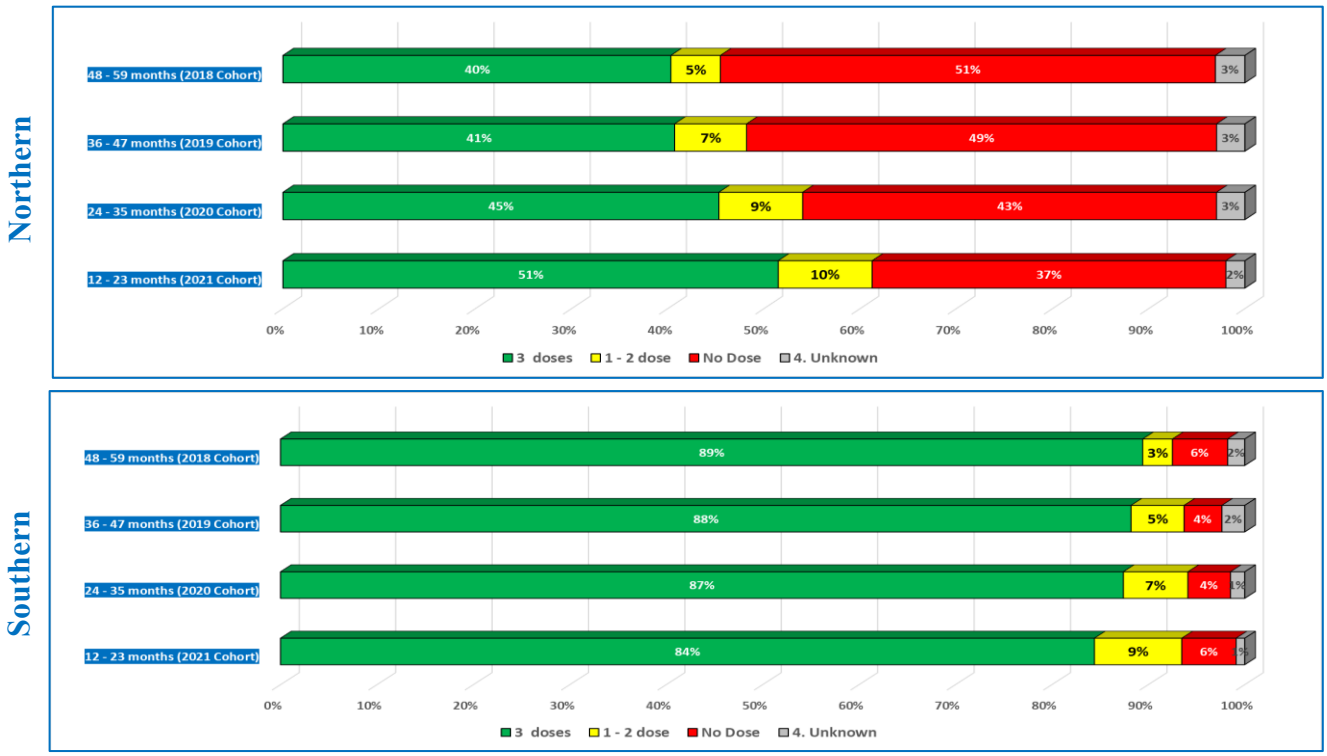
One of the challenges of the aggregated RI administrative coverage data is its limitation in analysing using inequality variables. Since the AFP data is case-based, it has the flexibility to analyse the data by equity stratification. To understand the progress made in immunisation coverage, the data were meticulously disaggregated by sex and geographical region within Nigeria, as illustrated in Table 1 and Figure 2.

Table 2: % three doses by Zone and gender using the 2020 cohort, 2022 AFP data

Zone	F	M	Gap (M-F)
NCZ	73%	66%	-7%
NEZ	43%	43%	0%
NWZ	35%	41%	+6%
SEZ	90%	88%	-2%
SSZ	75%	82%	+7%
SWZ	88%	95%	+7%
Nigeria	**55%**	**57%**	**+2%**

In the analysis of the 2020 age cohort (24 – 35 months old) from the 2022 Acute Flaccid Paralysis (AFP) data focusing on routine immunisation coverage, specifically the Oral Polio Vaccine (OPV3), a noteworthy discrepancy in the immunisation gaps between genders was observed in SSZ, SWZ and NWZ. The findings revealed that females in these three zones had at least a 6% gap in their OPV3 coverage compared to males. On the other hand, females had a higher proportion in NCZ and SEZ, with a 2% to 7% gap, highlighting the need for intensified immunisation strategies to ensure equitable health outcomes for all children. This also presents an area for further research into gender specific factors affecting vaccination programs.

Figure 4: Percentage of 3 doses with RI/OPV in Northern vs Southern States



The analysis indicates that in the northern states, the proportion of children receiving three doses of the Routine Immunisation (RI) with Oral Polio Vaccine (OPV) remains significantly low, falling below 52%. Despite this relatively low coverage, these northern states have consistently improved over recent years, suggesting targeted health initiatives may have a positive impact. In contrast, the southern states have recorded higher immunisation coverage rates; however, coverage has decreased from 2018 to 2021. This trend raises questions about the sustainability of maintaining the gains in these regions, necessitating a closer examination of factors contributing to the reduced rates and the effectiveness of the ongoing RI program.

Additionally, the study thoroughly examined and highlighted the disparities in vaccination coverage among children residing in nomadic versus non-nomadic settlements. Specifically, as illustrated in Table 3, there is a significant discrepancy in the proportion of children who have

received 3 OPV doses of the vaccine. This inequality in vaccination rates underscores the broader public health challenges faced by nomadic populations, who may have limited access to healthcare services compared to their non-nomadic counterparts. The findings emphasise the urgent need for targeted interventions to improve vaccination coverage in these underserved areas.

Table 3: RI/OPV doses of 4 – 59 months children by nomadic status, 2022 AFP data

Nomadic Status	>=3 doses	1 - 2 doses	Zero Dose	Unknown	Total
1-Nomadic	25%	8%	61%	6%	123
2-Non-Nomadic	59%	8%	29%	4%	7490
Grand Total	**59%**	**8%**	**30%**	**4%**	**7613**

Table 3 provides a comprehensive overview of the immunisation status of children residing in nomadic and non-nomadic areas concerning their Oral Polio Vaccine (OPV) administration through Routine Immunisation (RI). It reveals that only 25% of children in nomadic regions received the full three doses of OPV from the RI program, starkly contrasting with 59% of children in non-nomadic areas who completed the vaccination schedule. This discrepancy highlights a significant gap in vaccine coverage, pointing to potential barriers that nomadic populations face in accessing healthcare services.

Furthermore, the study emphasises the alarming situation regarding zero-dose children, those who have not received any doses of OPV. In nomadic areas, the proportion of zero-dose children stands at 61%, indicating that more than half of the children in these regions are unvaccinated. This statistic is particularly concerning as it reflects a critical public health issue where approximately 6 out of every 10 children in nomadic communities are left without basic immunisation against polio.

To further explore and elucidate the inequalities in vaccination coverage, the researchers conducted an in-depth analysis of RI/OPV doses categorised by urban and rural residency. Figure 3 illustrates the disparities in RI OPV vaccination rates between urban and rural areas across the six geopolitical zones, shedding light on the broader systemic issues contributing to these inequalities and underscoring the need for targeted interventions to improve immunisation access and uptake in underprivileged communities.

Figure 5: % RI/OPV doses for 4 – 59 months old AFP children

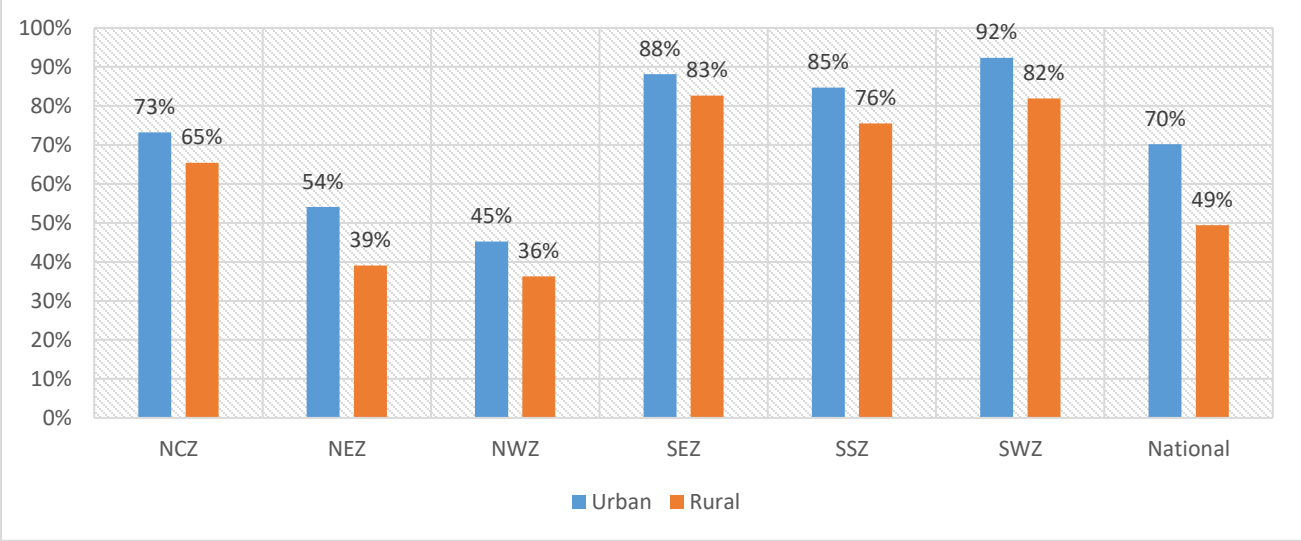
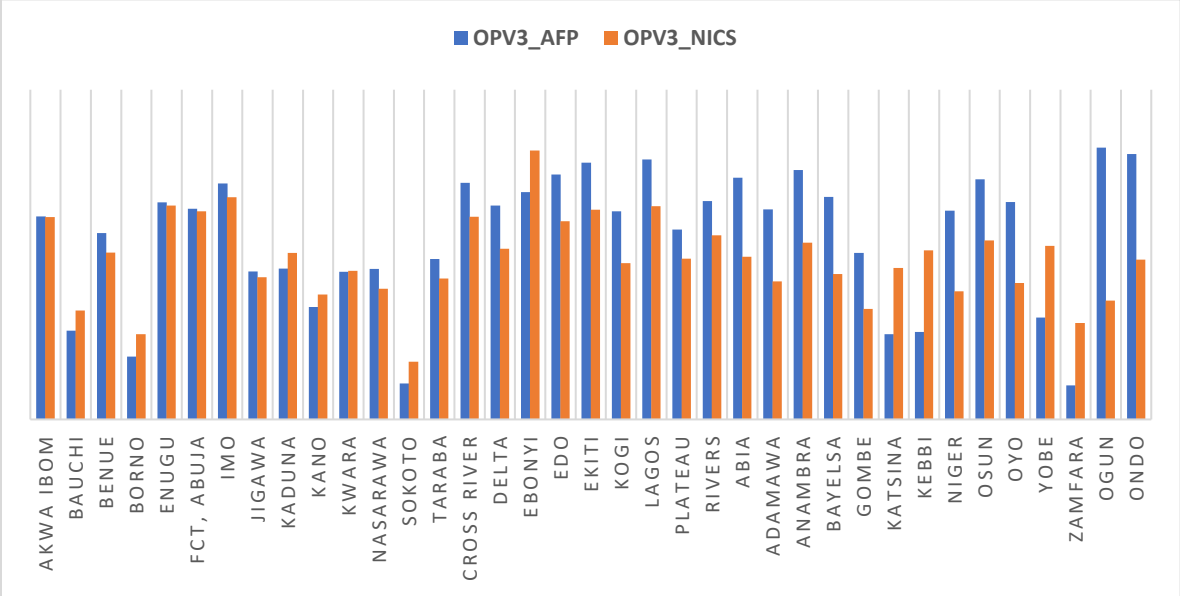


Figure 5 indicates a significant gap in the proportion of 3+ RI OPV doses in urban (70%) and rural (49%) areas. The gap ranges between 5% and 10% at the zonal level. The proportion of 3+ RI OPV doses is below 40% in NEZ and NWZ, where transmission dynamics of cVPV2 have been sustained in the last five years.

Further, the study has tried to compare the results of 3% doses of AFP in the 2020 cohort (24 – 35 months old children) with the 2020 RI coverage using the 2021 NICS result. Figure 4 shows the 2020 cohort of the 2022 OPV/RI coverage and 2020 OPV3 coverage in the 2021 NICS Data Analysis.

Figure 6: 2022 AFP and 2021 NICS RI OPV3 coverage for 2020 under one child



To understand the co-variables affecting immunisation coverage, a comparative analysis was conducted for the 37 states in Nigeria that participated in the 2021 NICS survey on routine immunisation coverage and the 2020 AFP cohort data. 14 states (Akwa-Ibom, Bauchi, Benue, Borno, Enugu, FCT Abuja, Imo, Jigawa, Kaduna, Kano, Kwara, Nasarawa, Sokoto, and Taraba) had RI OPV coverage within 10% gaps. Nine states (Cross River, Delta, Ebonyi, Edo, Ekiti, Kogi, Lagos, Plateau, and Rivers) had 11-20% gaps.

Additionally, 12 states (Abia, Adamawa, Anambra, Bayelsa, Gombe, Katsina, Kebbi, Niger, Osun, Oyo, Yobe, and Zamfara) were within 21-30% gaps. In contrast, two states had a gap greater than 30%, as shown in Table 3. Nationally, the gap between the OPV coverage estimate using AFP (56.4%) and the NICS coverage estimate (56.2%) in 2021 was 0.2%, which is less than 1%. The gap is wider at the sub-national level.

Table 4: 2022 AFP and 2021 NICS RI OPV3 percentage gaps by states.

% Gap States	# gap	Percentage	States
<=10% gap	14	38%	11 Northern 3 Southern states
11 - 20% Gap	9	24%	2 Northern and 7 Southern states
21 - 30% Gap	12	34%	7 Northern and 5 Southern states
>30% Gap	2	5%	2 southern states
National	**37**	**0%**	**37**

Table 4 summarises the gap by four categories at the state level. By comparing these data sets, the analysis aims to provide insights into how the OPV RI coverage estimate from AFP data is close to the NICS result and can be produced annually using each year's AFP data for operational planning and monitoring purposes, including inequality monitoring.

4.3. AFP Case-based Zero Dose Estimate

Annual estimates are generated to facilitate effective planning and diligent monitoring of immunisation programs. Specifically, the estimates derived from the OPV (Oral Polio Vaccine) data can play a crucial role in overseeing and evaluating new immunisation interventions implemented in targeted geographical areas. This approach allows health officials and policymakers to assess the coverage and effectiveness of ongoing vaccination efforts. Additionally, this comprehensive data analysis can pinpoint regions exhibiting concerning levels of immunisation coverage, thereby enabling targeted interventions. It can also help identify districts where a notable number of Acute Flaccid Paralysis (AFP) cases are reported among children under five years of age, which is critical for polio surveillance.

Furthermore, these districts often have a high prevalence of children who have not received any doses of the vaccine, referred to as high zero-dose children, categorised by cohort. The

accompanying Table 4 provides an in-depth analysis of missed vaccination opportunities among children aged 12-23 months and 24-35 months, offering detailed insights into gaps in immunisation coverage within these specific age groups, which is essential for strategising catch-up campaigns and improving overall coverage.

Table 5: Zero range for Affected LGA by Age Cohort

Zero-dose Range	Interpretation	Programmatic Suggestions	Affected LGAs	
			12-23 Months	24-35 Months
0-2	Low Risk	Maintain coverage, monitor and explore gaps	178	171
3-4	Moderate Risk	Investigate missed opportunities (e.g. Fixed & outreach failures)	46	46
5-7	High Risk	Prioritise gap analysis for improved microplanning and demand generation	20	39
8-14	Very High Risk	Use gap analysis data for intensive outreach, mobile sessions, and defaulters tracking	6	14
Total LGA			250	270

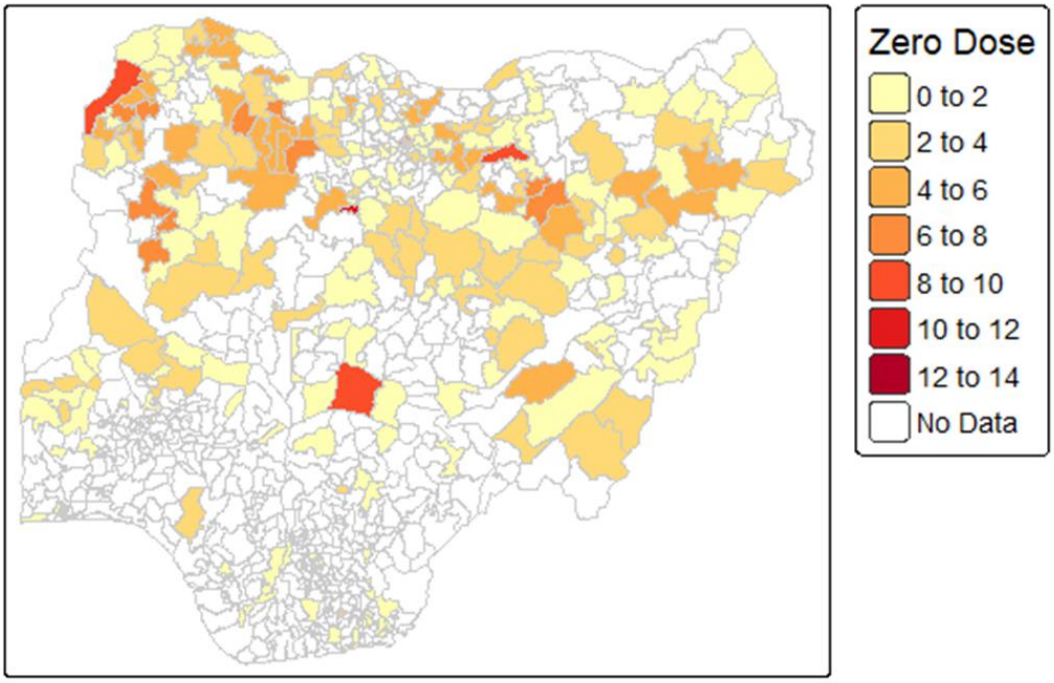
This comprehensive analysis aims to thoroughly evaluate the relative risk of active Acute Flaccid Paralysis (AFP) transmission within Local Government Areas (LGAs) that have zero-dose children, utilising a carefully selected proxy sample size of 7,613 individuals. The study places significant emphasis on estimating and interpreting the risks associated with different age cohorts, thereby providing a detailed and nuanced understanding of disease dynamics among populations at higher risk. Specifically, within the age cohort of 12 to 23 months, a total of 250 LGAs were identified as containing populations of zero-dose children, as visually represented in Figure 6, which is included below for reference.

These LGAs underwent rigorous statistical analysis employing the R programming language, a powerful and versatile environment known for its capabilities in data analysis, statistical computation, and visualisation.

The analysis involved calculating a virtualised relative risk metric for each of these areas, which are recognised as potential reservoirs for polio transmission, based on comprehensive data collected from AFP case surveillance. This approach enables a detailed understanding of both spatial and age-specific risk factors, thereby supporting the development of precise, targeted interventions and surveillance strategies.

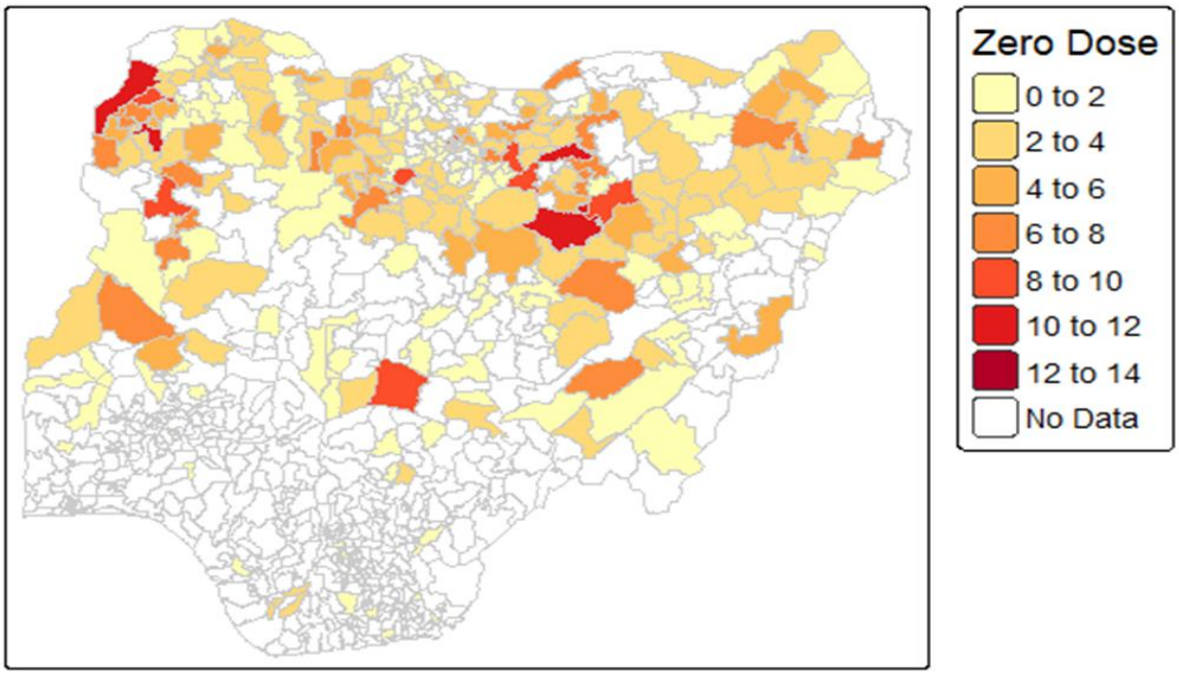
The ultimate goal of this detailed assessment is to reduce the incidence of AFP and to prevent future polio outbreaks through informed, data-driven decision making, facilitating more effective public health responses.

Figure 7: Map showing Zero-dose Children by LGA, (12-23 Months)



Additionally, a virtualised analysis was conducted on the age cohort of children between 24 and 35 months using the R programming language. This analysis is visualised in Figure 7 below. The purpose of this analysis was to identify geographic areas with specific characteristics, and it revealed that there are 270 Local Government Areas (LGAs) across Nigeria that have reported no cases of children with Acute Flaccid Paralysis (AFP) based on the data collected. This finding highlights potential gaps in surveillance or reporting, which could warrant further investigation to ensure comprehensive health monitoring.

Figure 8: Map of Nigeria showing Zero-dose Children by LGA, (24-35 Months)



4.4. Descriptive Modelling Findings

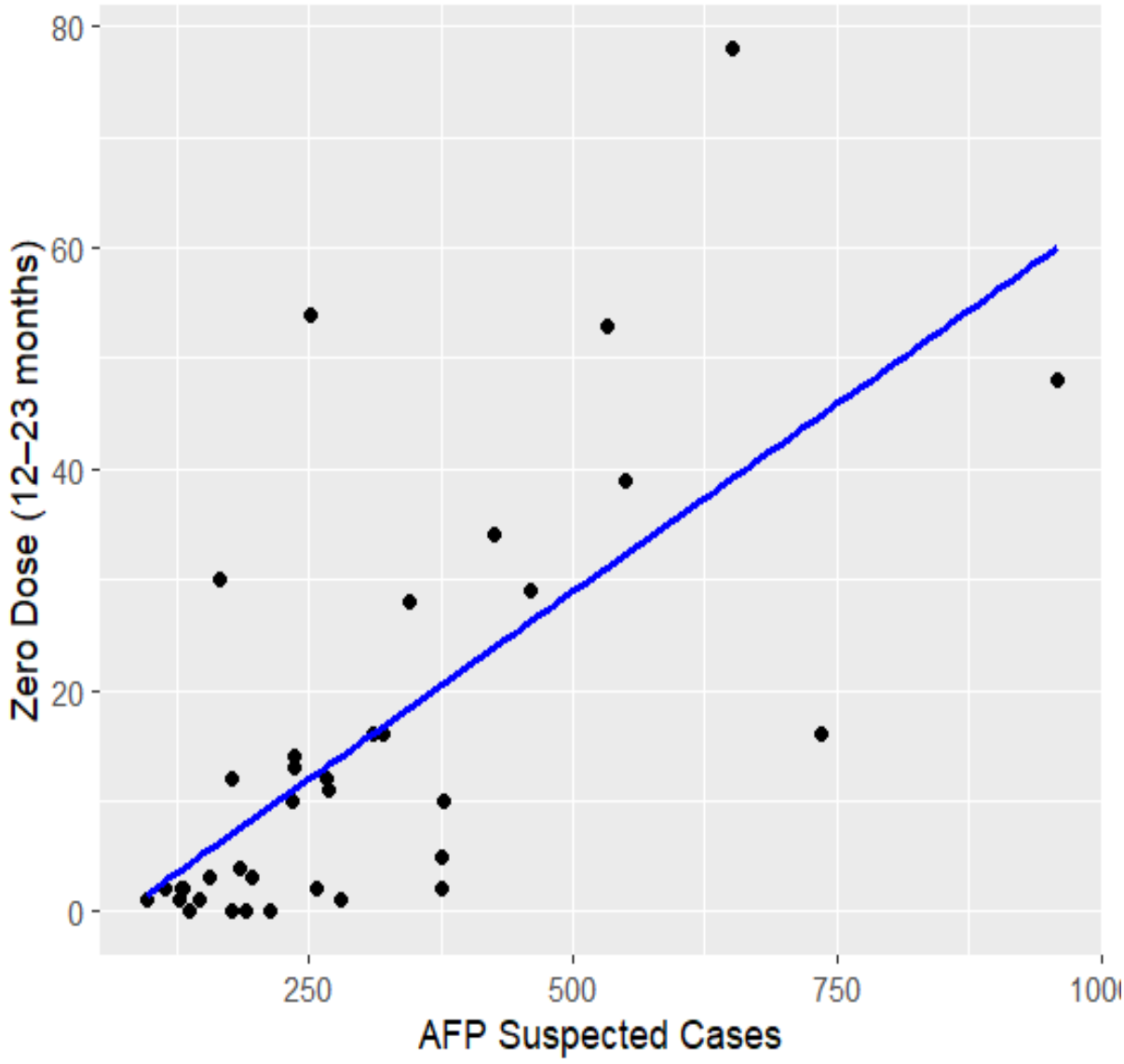
This study conducts a comprehensive descriptive analysis utilising past Acute Flaccid Paralysis (AFP) data alongside the National Immunisation Survey to assess the current burden of disease and coverage levels of Oral Polio Vaccine (OPV). Specifically, the analysis focuses on

data from the year 2022, including AFP reports and the National Immunisation Coverage Survey (NICS). The purpose is to explore the relationship between suspected AFP cases and zero-dose vaccine recipients. To achieve this, Pearson and Spearman correlation coefficients are calculated to examine the linear and monotonic relationships, respectively, between the number of suspected AFP cases and the zero-dose burden across different regions. This approach helps to identify patterns and potential correlations that could inform strategies for disease control and immunisation programs.

4.4.1. Pearson Correlation, AFP Cases, and Zero Dose Count

The figure below illustrates the results of a Pearson product-moment correlation analysis conducted to examine the relationship between suspected cases of Acute Flaccid Paralysis (AFP) and the prevalence of zero-dose children within two specific age cohorts: 12-23 months and 24-35 months. This correlation analysis aims to determine whether a statistical association exists between the number of AFP suspected cases and the proportion of children who have not received any doses of essential vaccines, thereby providing insights into potential patterns or correlations across these age groups.

Figure 9: AFP suspected Cases vs Zero dose (12-23 Months)



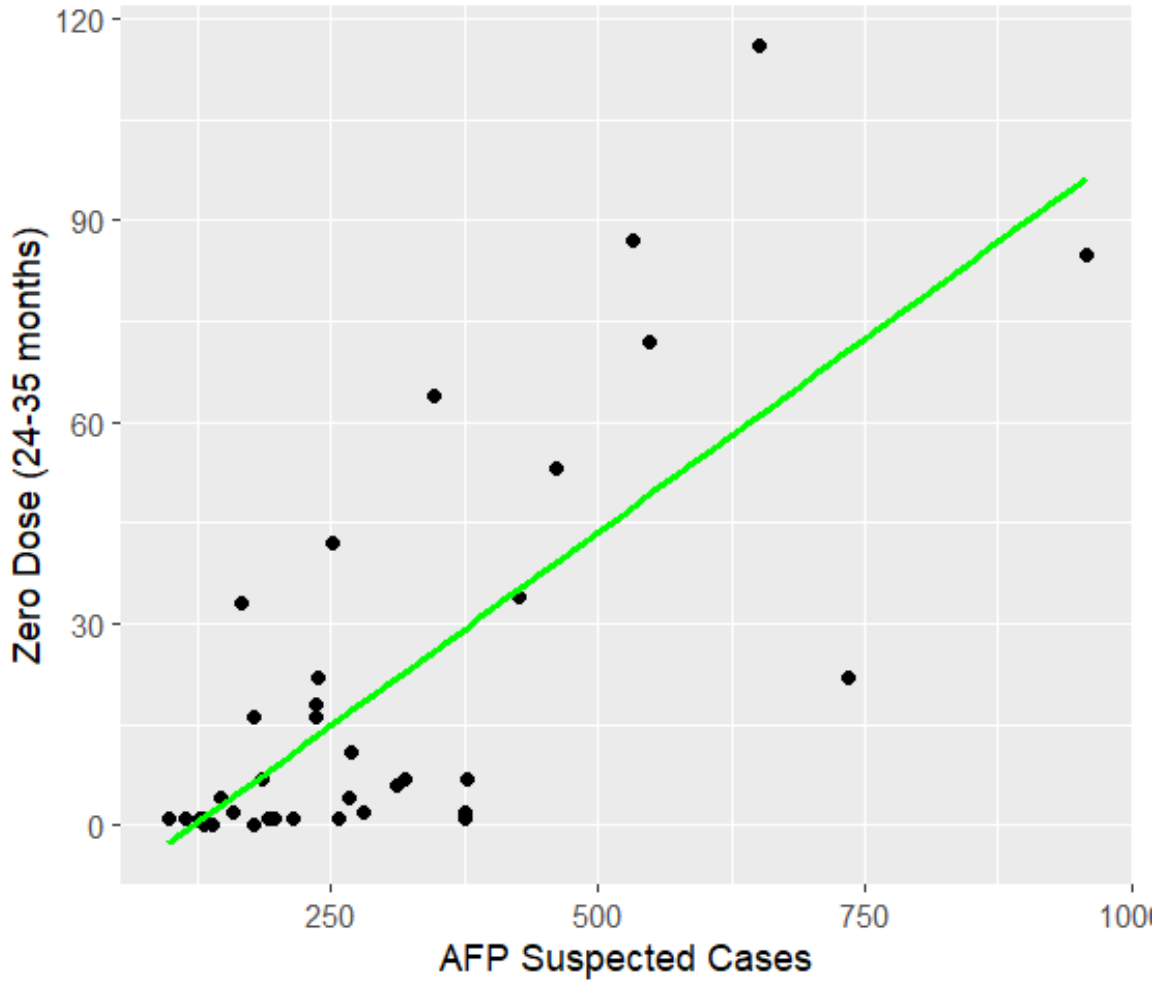
A Pearson product–moment correlation was calculated to evaluate the relationship between AFP suspected cases and zero-dose counts among children aged 24–35 months across states.

Correlation coefficient (r) = 0.733

$t(34) = 6.28$, $p < 0.001$

95% CI for r = [0.533, 0.855]

Figure 10: AFP suspected Cases vs Zero dose (24-35Months)



There is a strong, positive, and statistically significant correlation between AFP suspected cases and zero-dose prevalence in the 24–35-month age group. This indicates that states with higher zero-dose counts tend also to report more AFP suspected cases. The high correlation ($r \approx 0.73$) implies that poor vaccination coverage in this age group may be linked to increased AFP case reporting, potentially reflecting greater vulnerability to poliovirus or similar conditions among under-immunised populations. While this finding does not establish causation, it highlights a critical overlap between vaccination gaps and disease surveillance signals, suggesting that focusing on high zero-dose LGAs could also help reduce the AFP burden.

The study also controls for other factors (multiple regression), including population size, surveillance sensitivity indicators, or NICS coverage, to see if the relationship remains after adjusting for confounders. The study checked for non-linear patterns by fitting a Spearman correlation if the data might not be normally distributed.

4.4.2 Relationship between Zero-dose Children (24–35 months) and AFP Suspected cases

1. Linear Regression (LM) Findings

Model equation: ***AFP suspected cases = 203.92 + 4.67 x (zero-dose children, 24–35 months)***

For each extra zero-dose child (aged 24–35 months) reported, there is an average increase of approximately 4.67 AFP suspected cases across states.

Statistical significance:

The slope (4.67) is highly significant ($p < 0.001$), indicating a strong relationship.

$R^2 = 0.537$ → About 53.7% of the variability in AFP suspected differences in zero-dose counts alone can explain cases.

Intercept:

When the zero-dose count reaches zero, the model predicts approximately 204 AFP suspected cases, indicating that other factors also influence AFP case numbers.

2. Correlation (Spearman's Rank)

ρ (rho) = 0.683 → This shows a strong positive monotonic relationship between zero-dose counts and AFP suspected cases.

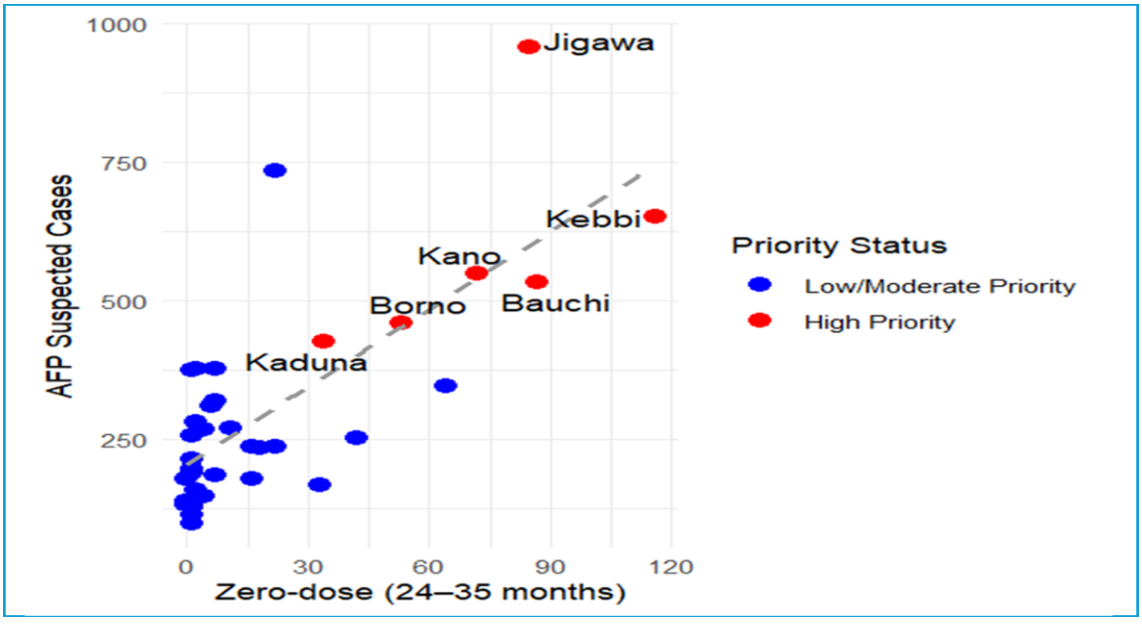
p-value = 4.41×10^{-6} → The correlation is statistically significant at $p < 0.001$.

This supports the regression finding, states with higher zero-dose counts also tend to have higher AFP suspected cases.

3. Implication for Prioritisation

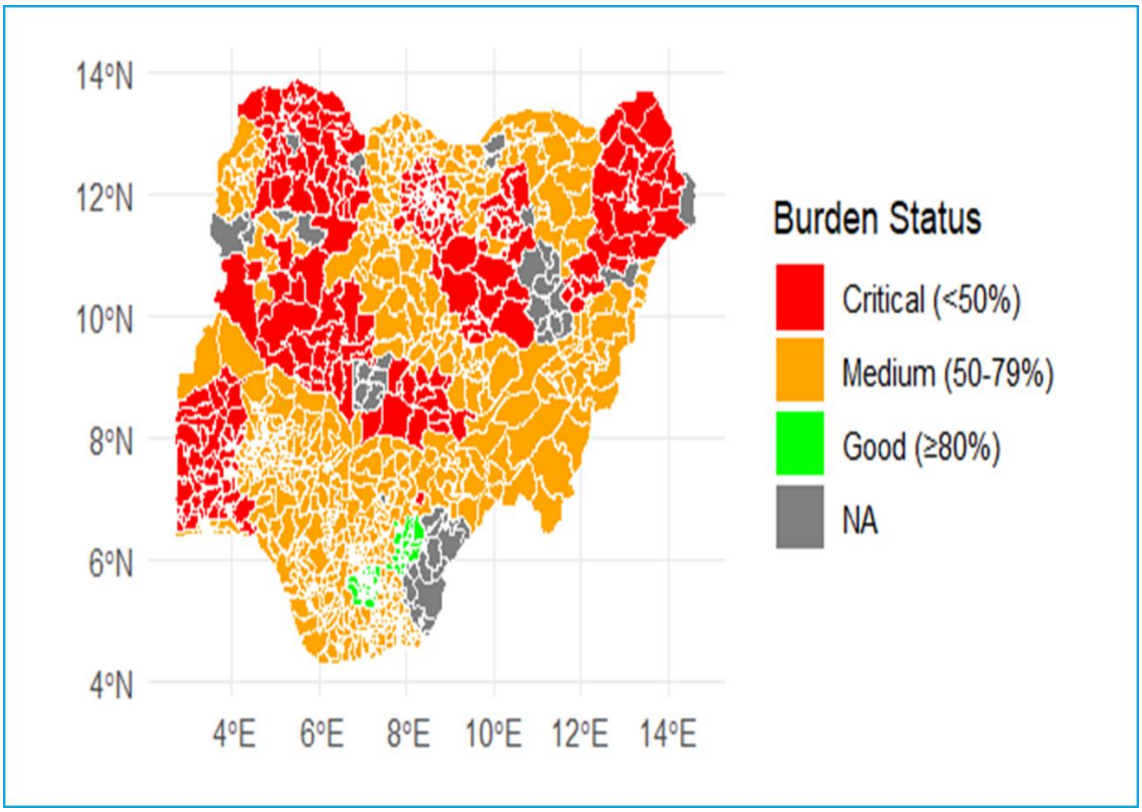
States with a higher number of zero-dose counts tend to also experience a greater burden of AFP (Acute Flaccid Paralysis) cases. This correlation suggests that missed immunisations, which are more prevalent in these states, may be linked to an increased frequency of reports of polio-like illnesses. The data imply that incomplete immunisation coverage could be a significant factor contributing to the spread and persistence of AFP cases. Consequently, prioritising and intensifying immunisation efforts in these high-burden, high-zero-dose states, such as implementing targeted campaigns, improving healthcare infrastructure, and community engagement, could have a substantial impact on reducing the incidence of AFP. As illustrated in Figure 7, focusing resources and strategies in these critical areas may lead to a notable decline in AFP cases, thereby strengthening overall disease control and eradication efforts.

Figure 11: High Priority States: Zero-dose (24–35 months) vs AFP Cases



The model showed the 24-35 months cohort from the 2022 AFP data as having a high correlation of zero-doses and suspected cases. Bauchi, Borno, Kano, Kaduna, Jigawa, and Kebbi states have a high tendency for continuous outbreaks of suspected cases and likely confirmed polio cases. The thesis also compares LGA OPV3 coverage burden status for three categories. We have 216 high-burden LGAs, 484 medium-burden LGAs, and 40 low-burden LGAs in Nigeria, as seen in Figure 8.

Figure 12:Polio Burden Status by LGAs Categorised by OPV3 Coverage, Nigeria

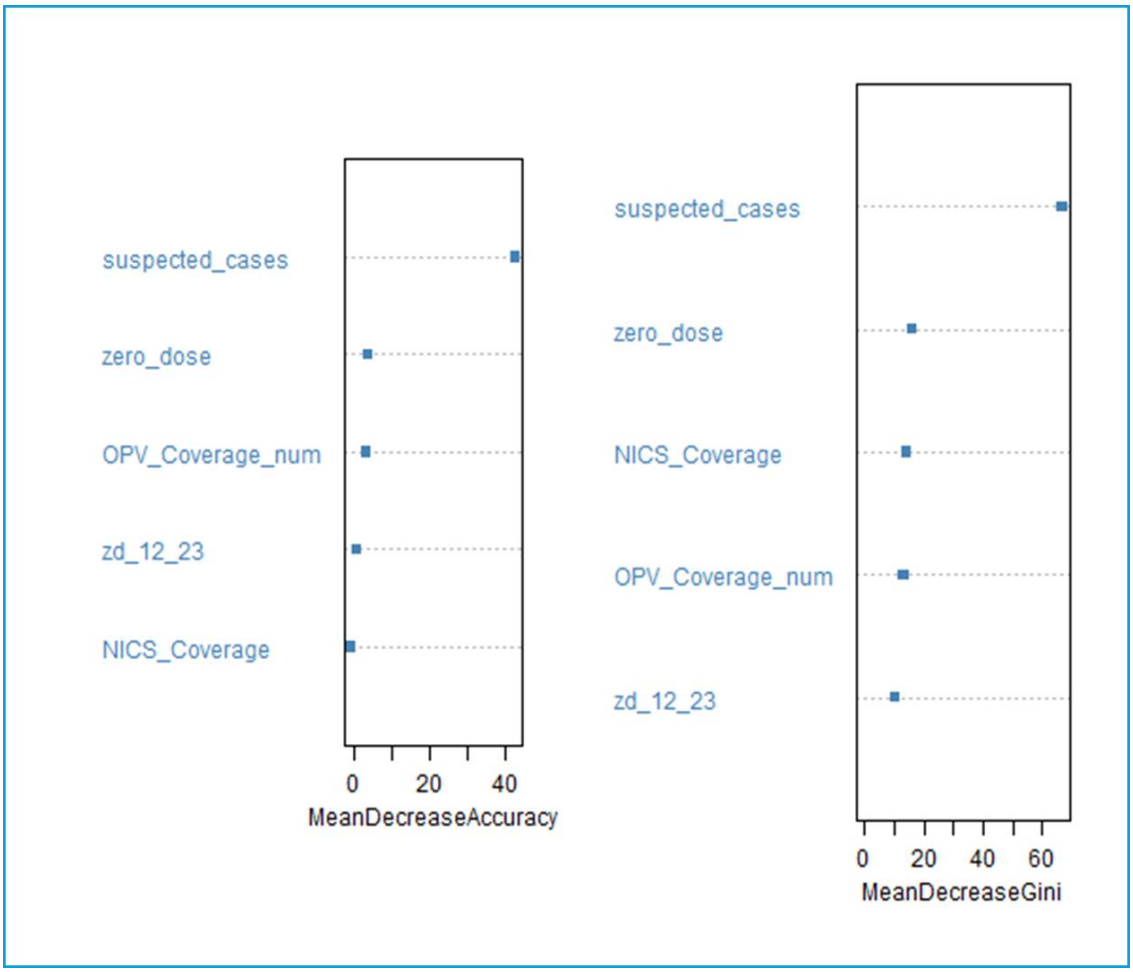


4.5. Predictive Modelling Analysis

The essence of the modelling analysis is used to answer objective three of the research, which aims to develop a statistical model for predicting or forecasting future status using AFP surveillance indicators, NICS coverage estimates, reported AFP cases, and zero-dose prevalence

predictors. Three data sets —AFP suspected cases by LGAs, AFP and NICS OPV coverage, and zero-dose children in LGAs for two age cohorts, were imported into the R Studio environment, merged, and cleaned to give a final data set for the modelling analysis. A predictive model for outbreak risk in LGAs was developed using a machine learning model to estimate the probability of outbreaks in these areas. A logistics regression analysis/random forest, and Hotspot analysis are conducted to identify variables that predict low, medium, and high outbreak potentials in LGAs.

Figure 13:Variable Importance (Mean Decrease Gini)



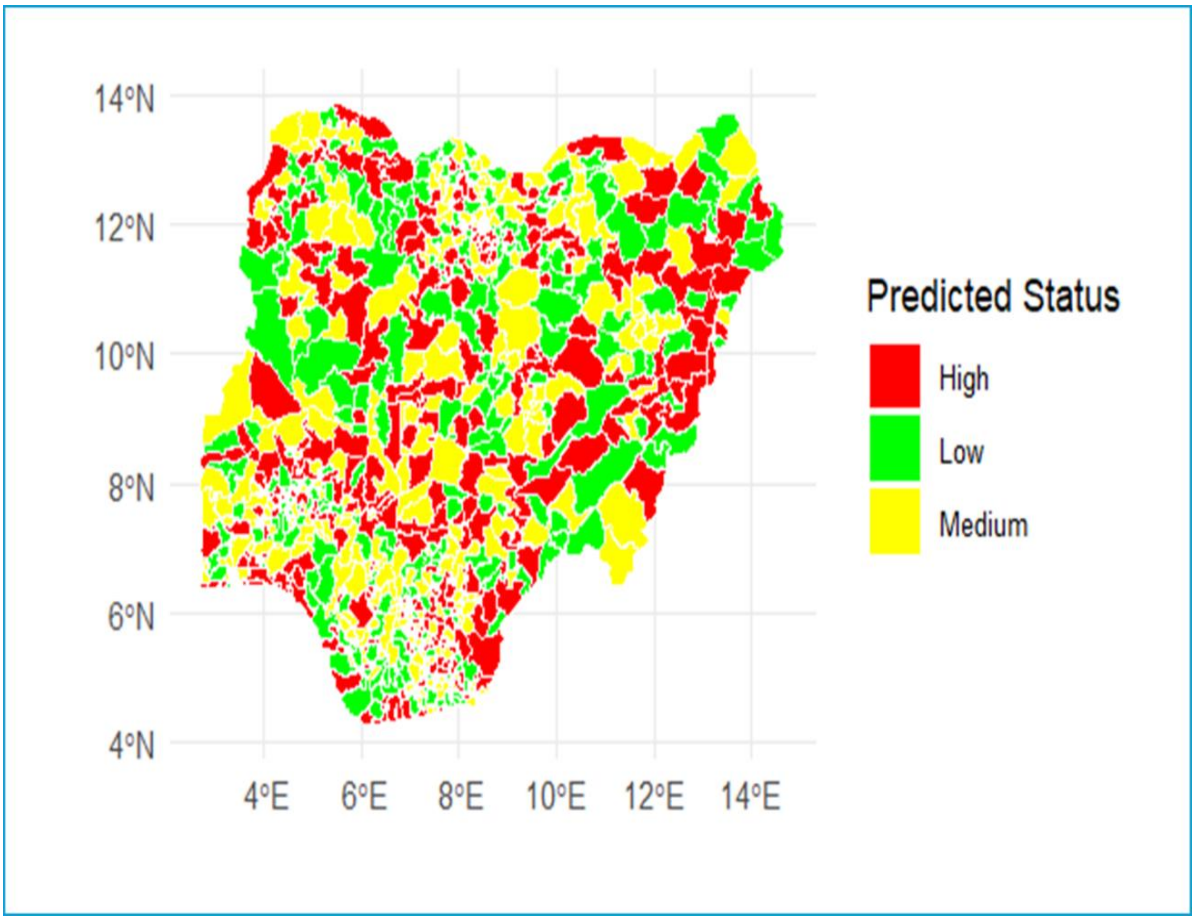
The random forest model was developed to categorise Local Government Areas (LGAs) as Low, Medium, or High poliovirus burden. It performed this classification using five predictor variables: OPV coverage, suspected cases, zero-dose children, zero-dose children aged 12–23 months, and NICS coverage. The model consisted of 500 decision trees, with two variables evaluated at each split. The out-of-bag (OOB) error rate was 17.89%, showing that the model correctly classified about 82% of LGAs during internal validation. This indicates fairly good predictive performance, although classification accuracy varied considerably across burden categories.

The confusion matrix shows the model's best performance was in the Low burden category, where it correctly identified 437 of 465 LGAs (error rate: 6.0%). In the Medium burden group, only 78 of 90 LGAs were accurately classified, with a high misclassification rate of 21.2%, primarily as Low burden. The High burden category classifies 5 of 23 LGAs.

From a public health perspective, the model’s capacity to accurately identify Local Government Areas (LGAs) with low, medium, and high burdens of disease plays a crucial role in optimising resource allocation. By pinpointing areas with higher risk, health authorities can concentrate more intensive field investigations and interventions where they are most needed, thereby improving the efficiency and effectiveness of disease control efforts. However, to improve the model's predictive accuracy specifically for high-burden LGAs, areas that are most critical for intervention, it is necessary to address the current imbalance in the training data, which may be skewed toward low- or medium-burden areas. This imbalance can be tackled through several strategies, such as oversampling the rare high-burden classes to ensure the model has enough examples to learn from, redefining the thresholds used to classify burden levels for better sensitivity, or incorporating additional relevant predictors.

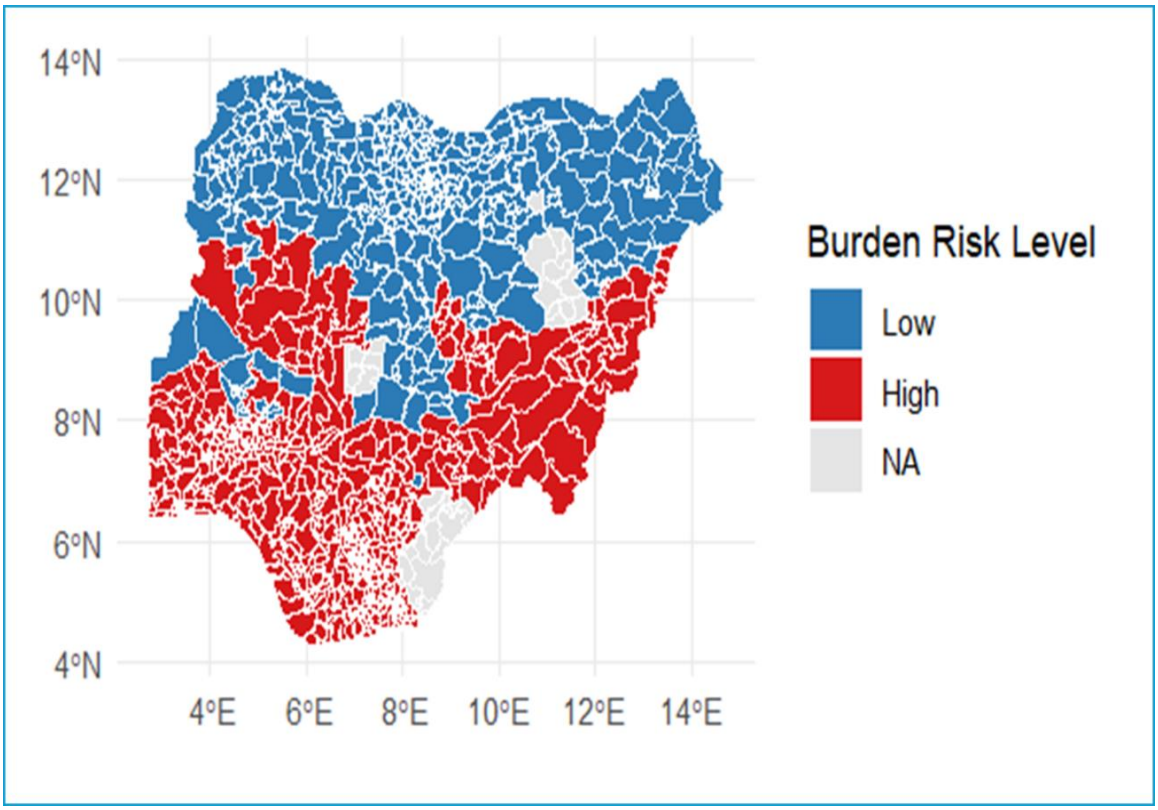
These predictors could include factors like population density, environmental surveillance results, the number of Acute Flaccid Paralysis (AFP) confirmed cases, routine immunisation coverage (RI), and supplementary immunisation activity coverage. The predictive burden map of Nigeria visualises this classification across various LGAs, illustrating the anticipated distribution of AFP outbreaks. This comprehensive approach allows for more targeted and effective public health responses, ultimately aiding in the containment and management of disease outbreaks.

Figure 14: Predictive Polio Burden Risk by LGA in Nigeria



The predictive analysis indicated a substantial likelihood of polio outbreaks occurring in 292 high-risk Local Government Areas (LGAs). These areas are predominantly situated along border regions and coincide with zones that have high zero-dose ratings, meaning a significant portion of the population has not received routine immunisations. Given these findings, these LGAs are identified as priority zones where resources and intervention efforts should be concentrated to prevent the spread of polio effectively. The study further enhanced its predictive approach by developing a model based on reported cases and various surveillance performance indicators, aiming to improve early detection and response mechanisms. The detailed results of this modelling process are illustrated in Figure 10, which visually depicts the risk levels across different LGAs and highlights the areas requiring additional predictors to understand the accurate risk level.

Figure 15: Polio Burden Risk by LGAs using Sensitivity of Surveillance

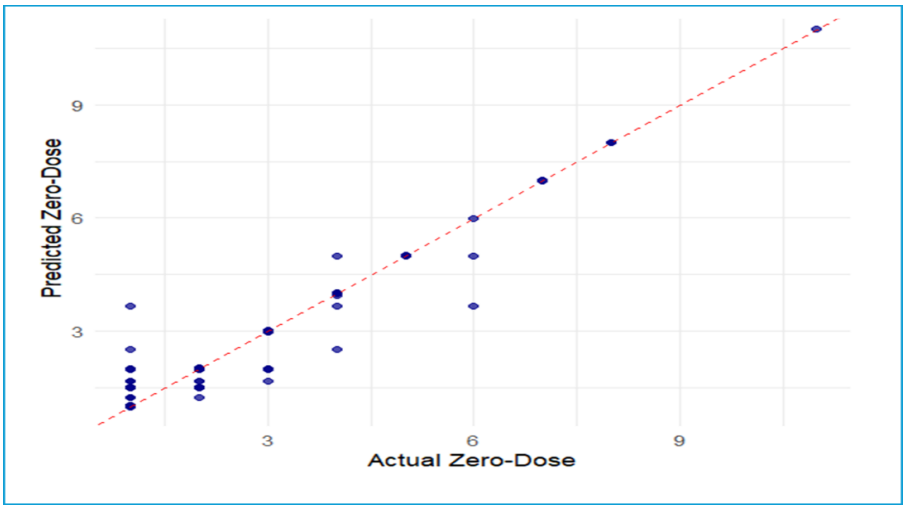


Using the 2022 suspected AFP (Acute Flaccid Paralysis) cases reported and surveillance sensitivity as the primary predictors, the analysis indicated that most northern states in Nigeria exhibited a low risk prediction. This low risk classification is primarily due to a higher number of reported cases in these northern regions compared to the southern regions. However, it is important to interpret these findings with caution.

A high sensitivity rate in surveillance, even in the absence of active confirmed cases, can potentially obscure the actual risk patterns. This phenomenon occurs because the surveillance system's high sensitivity may lead to numerous reported cases that do not necessarily correspond to actual cases of AFP, thereby masking areas that might be at higher risk. The random forest model employed for risk classification tends to categorise Local Government Areas (LGAs) as low risk based on these strong surveillance performance indicators, which may give a false sense of safety.

In the southern region, poor performance indicators for polio, heightened threats of insecurity in the Eastern part, and increased non-compliance with vaccination services and programs are of concern. The model has also suggested a high predictive potential for outbreaks in various LGAs if interventions are not implemented. Therefore, while the model shows promising surveillance indicators, it is crucial to consider other factors and data sources to accurately assess the true risk landscape of AFP in the region.

Figure 16: XGBoost Model of Predicted and Actual Zero-dose by Nigeria LGAs



Regression Model Results

Call:

lm(formula = zd_12_23 ~ OPV_Coverage_num + suspected_cases + NICS_Coverage, data = train_data).

Residuals:

Min	1Q	Median	3Q	Max
-3.6962	-0.9810	-0.3140	0.7102	8.0911

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.815806	0.475548	3.818	0.000190 ***
OPV_Coverage_num	-0.025888	0.007121	-3.635	0.000371 ***
suspected_cases	0.038641	0.006945	5.564	1.05e-07 ***
NICS_Coverage	0.016623	0.011583	1.435	0.153164

Signif. codes: 0 '' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1***

Residual standard error: 1.528 on 164 degrees of freedom (391 observations deleted due to missingness). Multiple R-squared: 0.2217, Adjusted R-squared: 0.2074; F-statistic: 15.57 on 3 and 164 DF, p-value: 5.872e-09

This linear regression model analyses how the proportion of zero-dose children aged 12–23 months (zd_12_23) relates to three predictors: OPV coverage (OPV_Coverage_num), suspected disease cases (suspected_cases), and NICS coverage (NICS_Coverage).

Key findings:

Intercept (1.82, $p < 0.001$): When OPV coverage, suspected cases, and NICS coverage are all zero, the model predicts a baseline zd_12_23 value of approximately 1.82 percentage points. OPV_Coverage_num (-0.0259, $p < 0.001$): Each 1% increase in OPV coverage corresponds to a roughly 0.026 percentage point reduction in the zero-dose proportion, indicating a significant inverse relationship consistent with the idea that higher OPV coverage decreases zero-dose children. Suspected_cases (0.0386, $p < 0.001$): Each additional suspected case per reporting period is linked to about a 0.039 percentage point rise in zero-dose proportion. This strong positive link suggests that areas with more suspected cases tend to have higher zero-dose rates, possibly pointing to gaps in service delivery or outbreak-related detection of missed children.

NICS_Coverage (0.0166, $p = 0.153$): Although the coefficient indicates a slight positive relationship, it is not statistically significant at the 5% level. Therefore, NICS coverage does not consistently predict zero-dose rates in this dataset.

Model performance:

The model accounts for approximately 22.2% of the variance in zero-dose prevalence, with an Adjusted R^2 of 20.7%. It is statistically significant overall ($F(3,164) = 15.57$, $p < 0.000000006$), suggesting that the predictors, as a group, are influential in explaining differences in zero-dose rates.

Interpretation:

Higher OPV coverage significantly reduces the risk of high zero-dose prevalence, whereas higher suspected case counts are associated with increased risk. Although NICS coverage is linked to immunisation performance, it did not demonstrate a significant independent effect in this model. The moderate R^2 value indicates that other unmeasured factors, like access to services, geographic barriers, or socio-economic conditions, may also play a crucial role.

4.6. Modelling Vaccine Intervention Impact from 2022 AFP and NICS Datasets

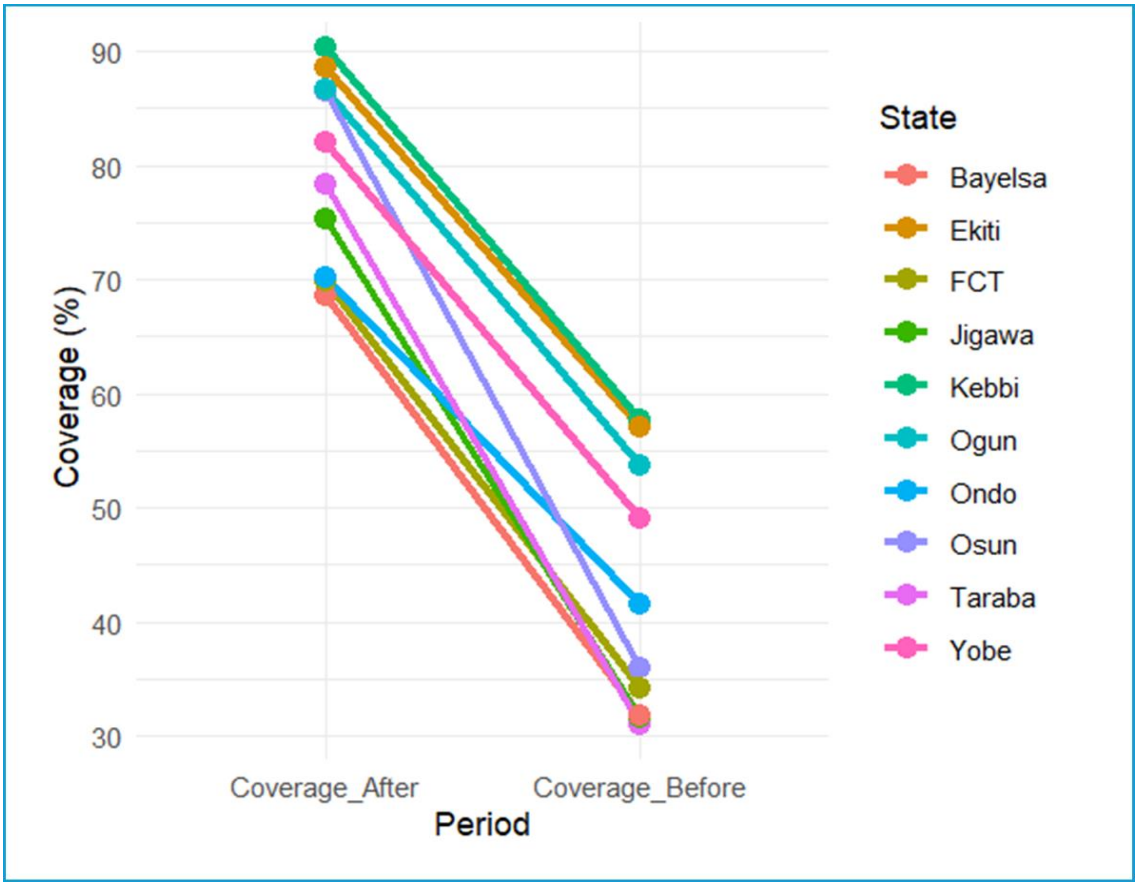
Results of the Vaccine Intervention Analysis

The analysis assessed the impact of vaccine interventions across Nigerian states and Local Government Areas (LGAs) using available coverage data before and after the intervention. Three complementary approaches were used: regression modelling of determinants, identification of the top ten LGAs with the highest intervention gains, and a state-level heatmap showing variation in impact across all 37 states. Together, these methods provide a comprehensive picture of intervention effectiveness, geographic variation, and underlying drivers.

Top Ten States with the Best Intervention Impact

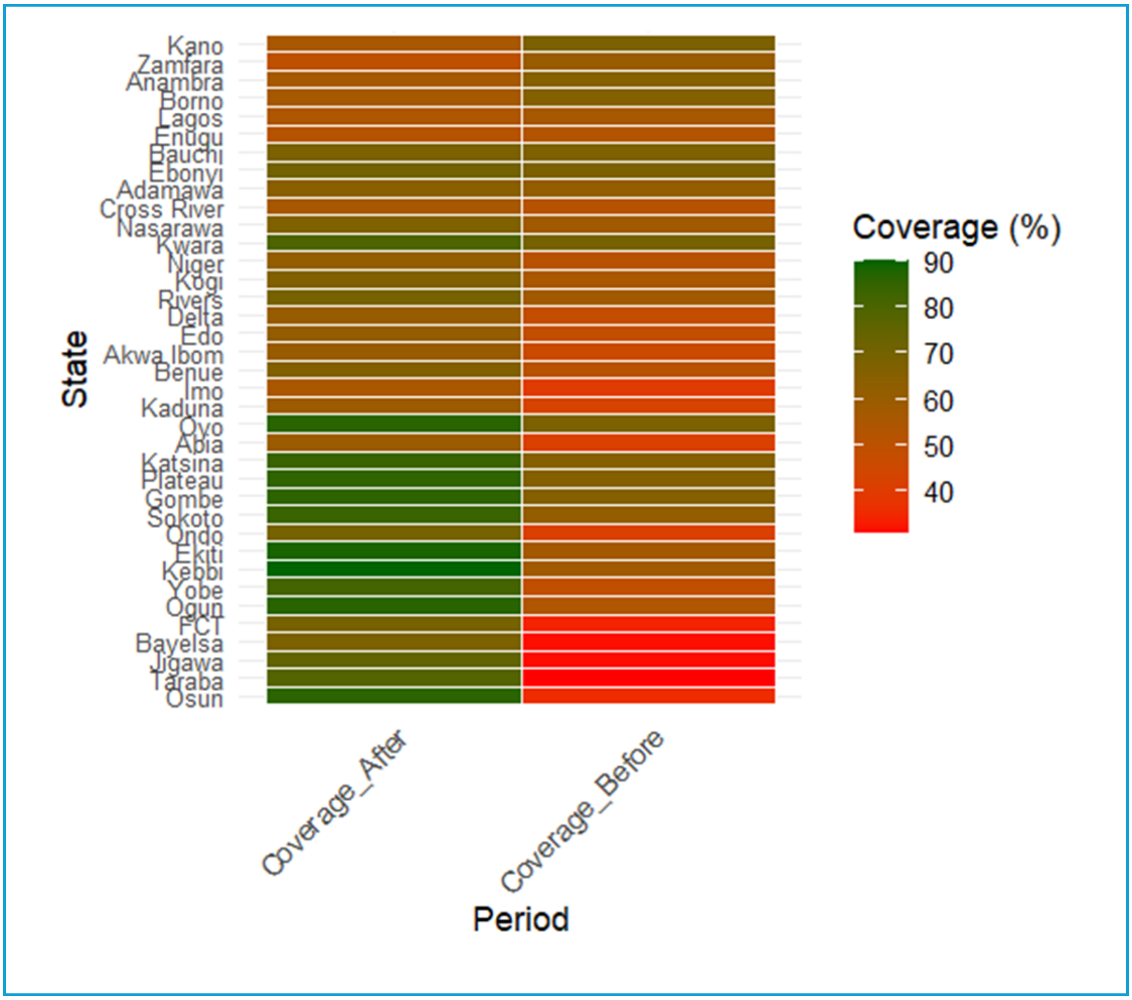
The analysis demonstrates vaccine coverage improvement from the RI service programme and SIA activities to highlight LGAs with the greatest intervention impact. The data analysis reveals patterns indicating where intervention should be maintained or where strategies need to change if they are creating a negative effect on immunisation coverage. While this may not reflect an overall improvement in the state's coverage, it emphasises the need to sustain interventions in these States.

Figure 17: Top 10 States with Best Vaccine Intervention Impact over time



The state-level analysis sought to pinpoint areas with the most significant improvements in vaccine coverage. By measuring the change in coverage before and after the intervention, the ten top-performing states were identified. The findings reveal that these states achieved notable increases, with some exceeding 20 percentage points. Plotting coverage levels pre- and post-intervention confirmed that the effects were substantial rather than minor. Importantly, this indicates that the programme's success was not confined to a single region. The states with LGAs in the top ten exemplify best practices and could provide valuable insights for expanding intervention strategies across the country. Figure 14 shows the heatmap of this pattern in the states.

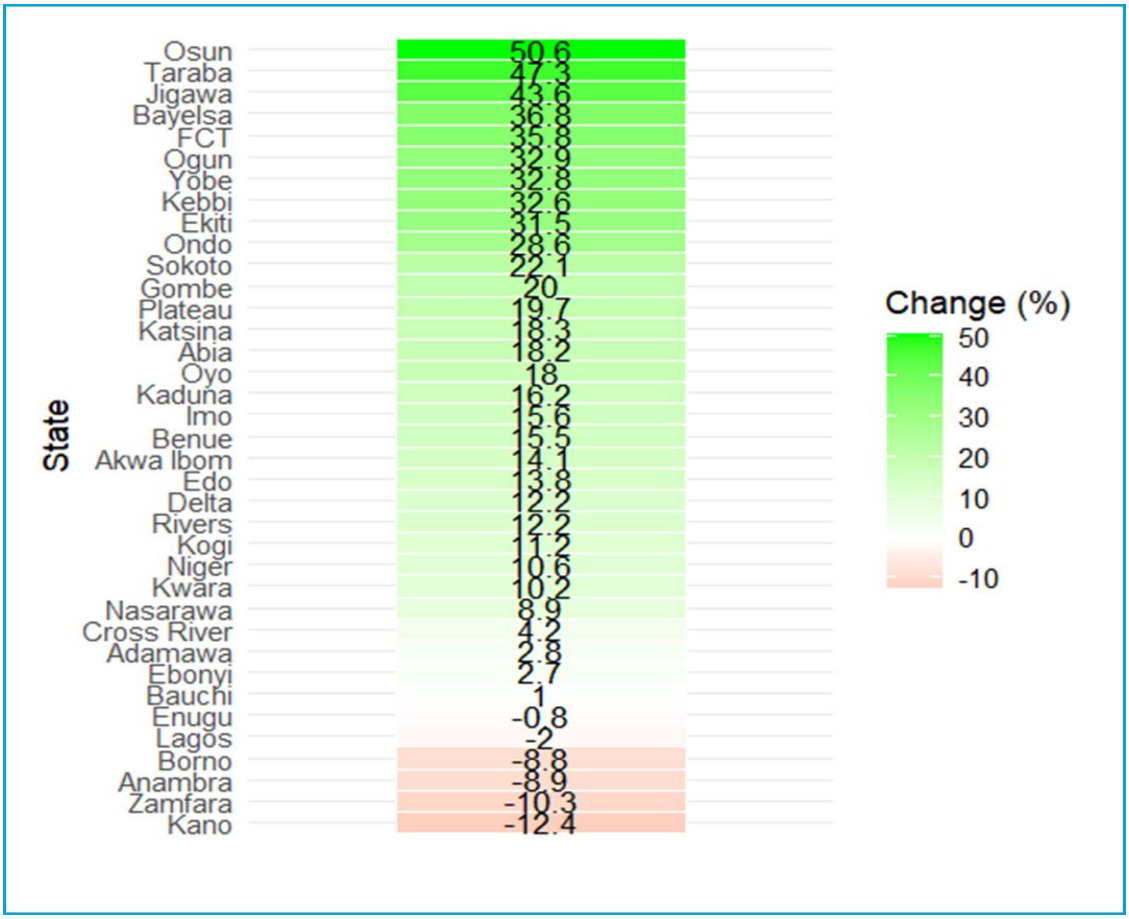
Figure 18:Heatmap of vaccine coverage before and after intervention



State-Level Heatmap of Intervention Impact

When the impact of interventions was summarised at the state level and visualised with a heatmap, a different perspective emerged. Some states showed steady increases across most regions, while others had mixed or minimal progress. The heatmap provided context for the findings of the top ten states, illustrating that local success does not always translate to statewide improvements. For example, a state might be in the top ten because of one highly successful region but still have uneven overall performance. States with negative impacts demonstrate that interventions are ineffective and necessitate a change in strategies. This shows that intervention success varies and depends on local implementation conditions.

Figure 19: Change in Vaccine Coverage after intervention by States in Nigeria



Several limitations should be acknowledged. First, the analysis is constrained by missing data: nearly 400 observations were excluded from the regression model due to incomplete reporting, which affects the generalisability of the findings. Second, data sources vary in quality and may include measurement errors or under-reporting, particularly in conflict-affected or hard-to-reach areas. Third, focusing on the top ten LGAs emphasises relative change, which may overstate improvements in areas that started with very low coverage but still remain below target thresholds. Fourth, aggregating data at the state level can obscure successes or failures at the LGA level, and vice versa. Lastly, the cross-sectional design cannot fully assess whether improvements are sustainable over time; additional follow-up is necessary to confirm if gains are maintained. Therefore, the study also conducted a Time trend analysis using additional RI data for 2023 to 2024 from OPV0-OPV3 coverage, and the surviving infant population by LGA.

4.7. Time-Series Coverage Analysis

A time-series coverage data (2022, 2023, 2024) for OPV0–OPV3 alongside population at the LGA level offers a more robust predictive analysis for monitoring future coverage patterns. This measures a baseline, intervention and post-intervention timeline. The analysis will compute the Year-to-Year change in coverage per LGA, the Average annual growth rate (AAGR) in coverage, and identify LGAs with sustained improvement versus those that stagnate/decline. Using the surviving infant data from 2023 – 2024, we calculated the absolute numbers of children reached/missed. The study predicted coverage in 2025 using linear trend regression (lm) and Mixed-effects models, accounting for State/LGA clustering.

4.7.1. Datasets for Time-series Model

- RI coverage data (2022–2024): Routine immunisation reports (OPV0–OPV3, population).
- AFP surveillance data: Captures OPV doses received by children <15 years (validated by case investigations). This is a form of independent verification of RI coverage.
- NICS survey data (2022): Provides gold standard, population-based estimates of coverage (with sampling error). Baseline data set
- Surviving Infants Population (2023 and 2024)

The study aimed to correct bias by validating RI administrative coverages using baseline data—NICS 2022 and AFP case-based surveillance data—to assess whether the RI coverage in 2022 was overestimated or underestimated. The researcher applied calibration factors, such as adjusting RI coverage downwards based on median differences observed in NICS or AFP data. Subsequently, a triangulation was carried out by comparing the coverage data from 2022 across RI, AFP, and NICS sources.

The analytical approach was involved.

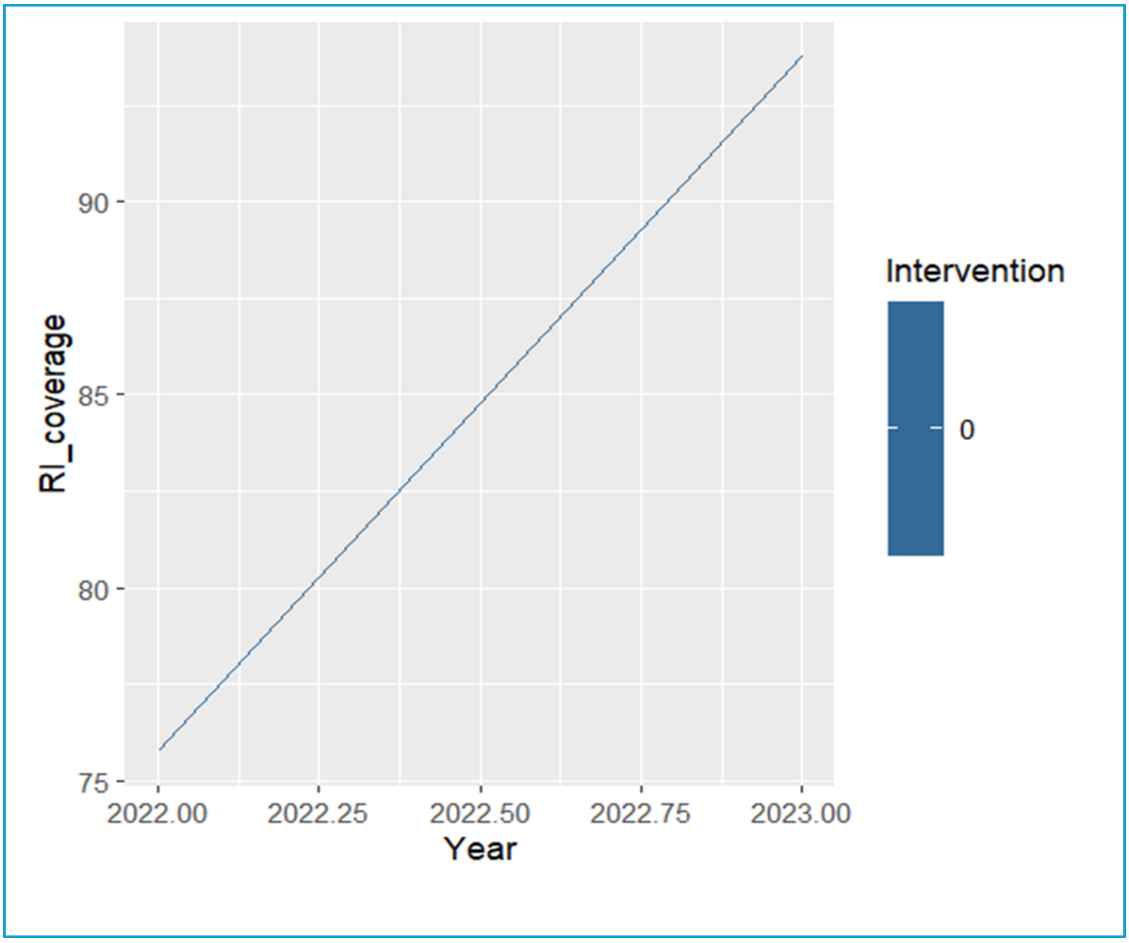
a) Difference-in-Difference with Anchoring: using NICS 2022 as the baseline "true" coverage to measure changes in RI coverage relative to that benchmark. It then compared intervention with non-intervention LGAs using the difference-in-difference method.

b) Predictive Models: Using AFP and RI combined as predictors, with NICS 2022 as the target (dependent variable), to develop a correction model through regression or mixed-effects analysis.

c) Measuring Intervention Impact: This compares year-on-year changes in adjusted coverage (anchored by NICS, verified by AFP). Estimate the number of children reached versus missed using the population, then rank LGAs by the absolute number of children reached (not just percentage).

4.7.2. Difference in Difference Anchoring

Figure 20: RI Coverage overtime by Intervention Status



A linear regression model was fitted to assess the association between routine immunisation (RI) coverage and the combined effects of intervention status and year. The

dependent variable was RI coverage, while the independent variables were Year, Intervention, and their interaction (Intervention with Year). The model revealed a statistically significant effect of Year on RI coverage ($\beta = 17.99$, SE = 1.58, $t = 11.36$, $p < 0.001$). This indicates that, on average, RI coverage increased by approximately 18 percentage points per year across the study period, independent of intervention status. The intercept was negative ($\beta = –36{,}292.47$, $p < 0.001$), which is not interpretable in a substantive sense given the coding of Year, but reflects the baseline adjustment required by the model.

Notably, the coefficients for Intervention and Intervention with Year were not estimated because of perfect collinearity (singularities). This suggests that in the dataset, Intervention is either completely confounded with Year (e.g., introduced in only one year or all LGAs received the same intervention simultaneously) or lacks sufficient variability across the study period to permit estimation of its independent effect.

As such, the model effectively reduces to a simple regression of RI coverage on Year. The model explains only a modest proportion of the variance in RI coverage (Adjusted $R^2 = 0.074$), suggesting that while coverage clearly improved over time, other unmeasured factors such as surveillance quality, program intervention dynamics, population shifts, or campaign intensity may also play important roles.

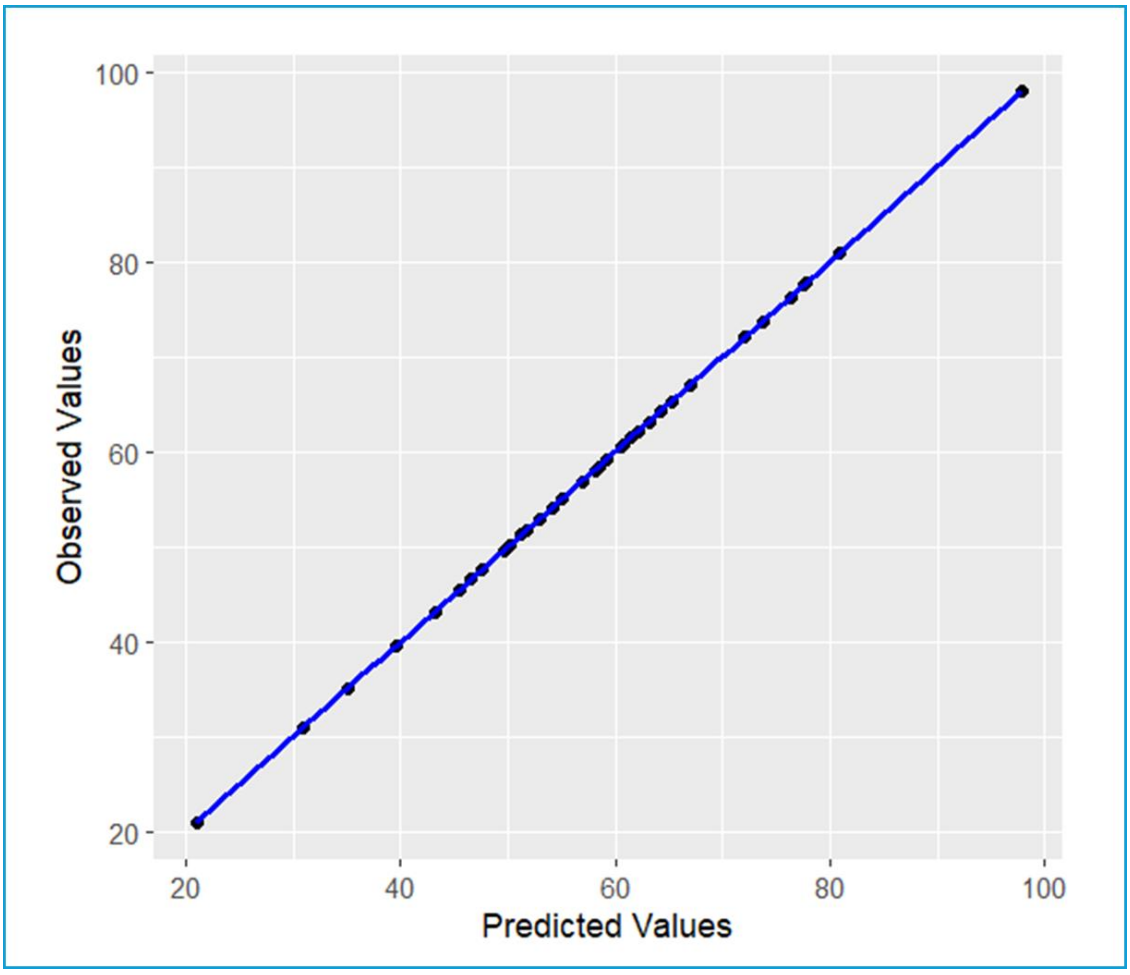
In summary, RI coverage significantly improved across years, but the model was unable to quantify the independent contribution of interventions due to data structure limitations. Further analysis, possibly stratifying by LGA or adjusting for NICS survey benchmarks, may help disentangle temporal improvements from true intervention effects. The next section predicts or forecasts coverage over the years.

4.7.3. Predictive Models

Interpretation of Predictive Model

A linear regression model was developed to predict NICS OPV3 coverage (from survey data) using two explanatory variables: AFP OPV3 coverage (administrative/reported coverage from AFP monitoring) and AFP cases (number of acute flaccid paralysis cases), as seen in Figure 21.

Figure 21: Model Fit Predicted over NICS OPV3 Coverage observed values



The model demonstrates a strong and statistically significant relationship between AFP OPV3 coverage and NICS OPV3 coverage. The coefficient for AFP OPV3 is 0.39 ($p < 0.001$), which suggests that for every 10-percentage point increase in AFP OPV3 coverage, the predicted NICS OPV3 coverage increases by about 3.9 percentage points, holding AFP cases constant. This finding indicates that AFP OPV3 coverage, while not perfectly aligned with NICS survey estimates, is a meaningful predictor of immunisation performance at the population level. The coefficient for AFP cases is 0.071, with a p-value of 0.055. This indicates a marginal, borderline-significant association. Interpreted substantively, it suggests that each additional AFP case detected in an LGA is associated with a 0.07 percentage-point increase in predicted NICS OPV3 coverage, though this effect is weak and may reflect underlying surveillance intensity or population size rather than a direct causal relationship.

The intercept of 31.25 is highly significant ($p < 0.001$). This represents the baseline predicted NICS OPV3 coverage when both AFP OPV3 coverage and AFP cases are zero. While not realistic in practice, it serves as the model's baseline constant and helps calibrate predictions. The model explains approximately 41% of the variance in NICS OPV3 coverage (Adjusted $R^2 = 0.408$). This indicates moderate predictive power: AFP OPV3 coverage and AFP case counts together account for nearly half of the variability in survey-measured OPV3 coverage across LGAs. However, a large portion of variation remains unexplained, suggesting that additional predictors—such as zero-dose estimates, routine immunisation service availability, socioeconomic factors, or campaign intensity- would improve model performance. The residual standard error of 11.27 implies that predictions deviate, on average, by about ±11 percentage points from observed NICS values.

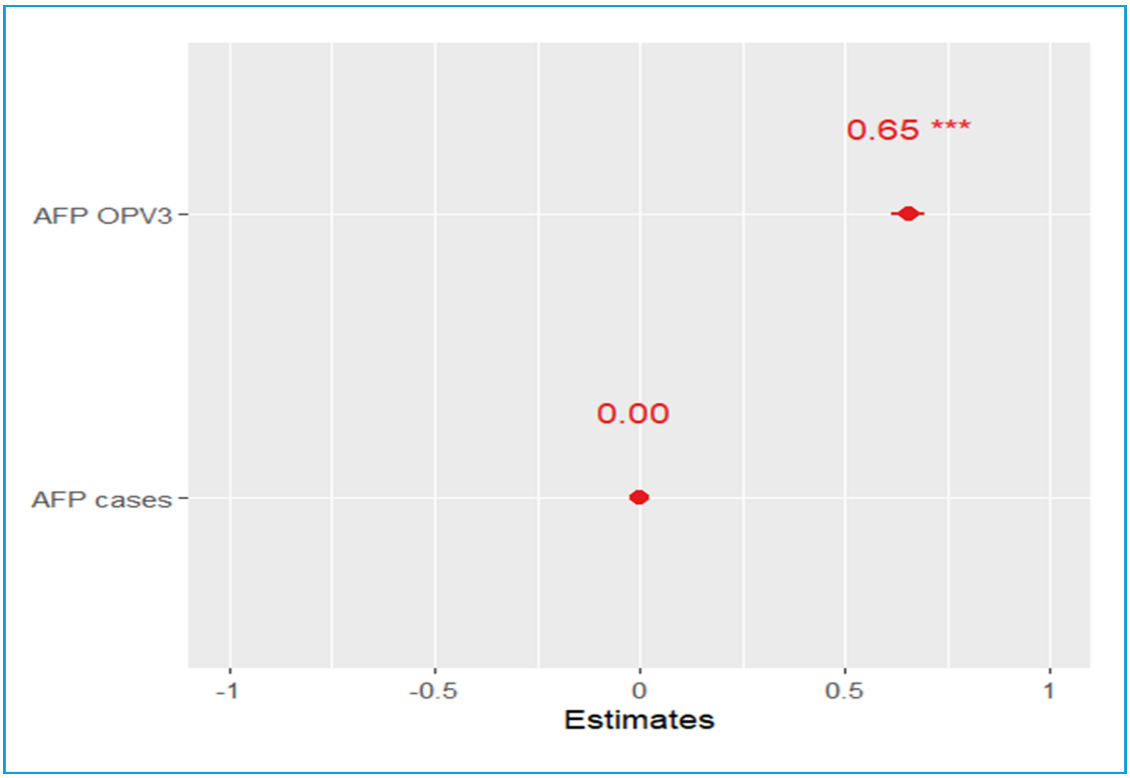
Overall, AFP OPV3 coverage is a strong predictor of NICS OPV3 coverage, confirming the utility of administrative data for predictive modelling. AFP case counts show only a marginal contribution. The model is helpful for approximating NICS outcomes where survey data are lacking, but further refinement with additional predictors would strengthen its reliability for programmatic decision-making. The next section shows that the random effect is adjusted with the AFP OPV3 data as predictors.

Interpretation of the Mixed-Model

The linear mixed-effects model was specified to predict NICS OPV3 coverage (from household survey data) using AFP OPV3 coverage and AFP case counts as predictors, while including state as a random intercept to account for between-state variability. This structure allows the model to capture differences across states while still estimating the overall effects of AFP indicators on NICS outcomes. The fixed-effects results indicate that AFP OPV3 coverage is a strong and highly significant predictor of NICS OPV3 coverage.

The estimated coefficient is 0.65, meaning that for every 10-percentage point increase in AFP OPV3 coverage, the predicted NICS OPV3 coverage increases by approximately 6.5 percentage points, after adjusting for state-level clustering. This strengthens the evidence that AFP-based administrative data is a reliable proxy for predicting survey-based immunisation outcomes, particularly when state-specific effects are considered, as seen in Figure 22 below.

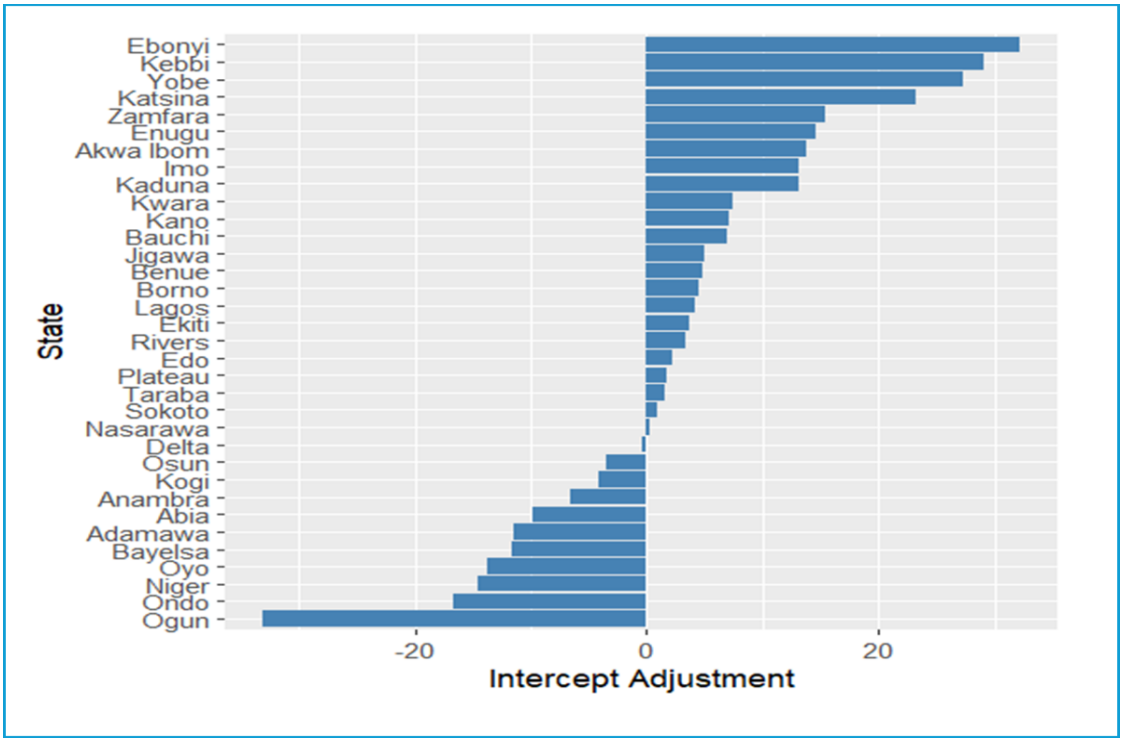
Figure 22: Fixed-effect estimate for AFP OPV3 Coverage



In contrast, the effect of AFP case counts is negligible. The estimated coefficient is extremely close to zero (1.18e-13) with no statistical significance, suggesting that AFP case counts do not provide additional explanatory power for NICS coverage once AFP OPV3 coverage and state-level variation are included. This may reflect the fact that AFP case counts are more influenced by surveillance intensity and population size than by vaccination coverage itself. The random-effects results show that the variance between states is 9.03, corresponding to a standard deviation of about 3.0 percentage points in the intercepts. This means that states differ systematically in their baseline levels of NICS OPV3 coverage, independent of AFP OPV3 performance. Accounting for this heterogeneity improves the robustness of the predictions and avoids overstating the influence of AFP coverage alone. The residual variance is minimal (≈ 0), indicating that most of the unexplained variation is absorbed by the state random effect.

However, the model diagnostics highlight potential convergence issues and recommend rescaling variables. This suggests that although the model fits well, numerical instability could affect the accuracy of estimates, and further refinements (such as centring predictors or simplifying the model) might improve reliability. Overall, the mixed model confirms that AFP OPV3 coverage is a strong predictor of NICS OPV3 coverage, with notable state-level differences impacting results. AFP case counts do not significantly contribute. This modelling approach improves predictive validity for programme use by recognising and quantifying inter-state heterogeneity in immunisation performance. The study also examined the quality of administrative data using random effects estimates.

Figure 23: Random Intercept by State in Nigeria

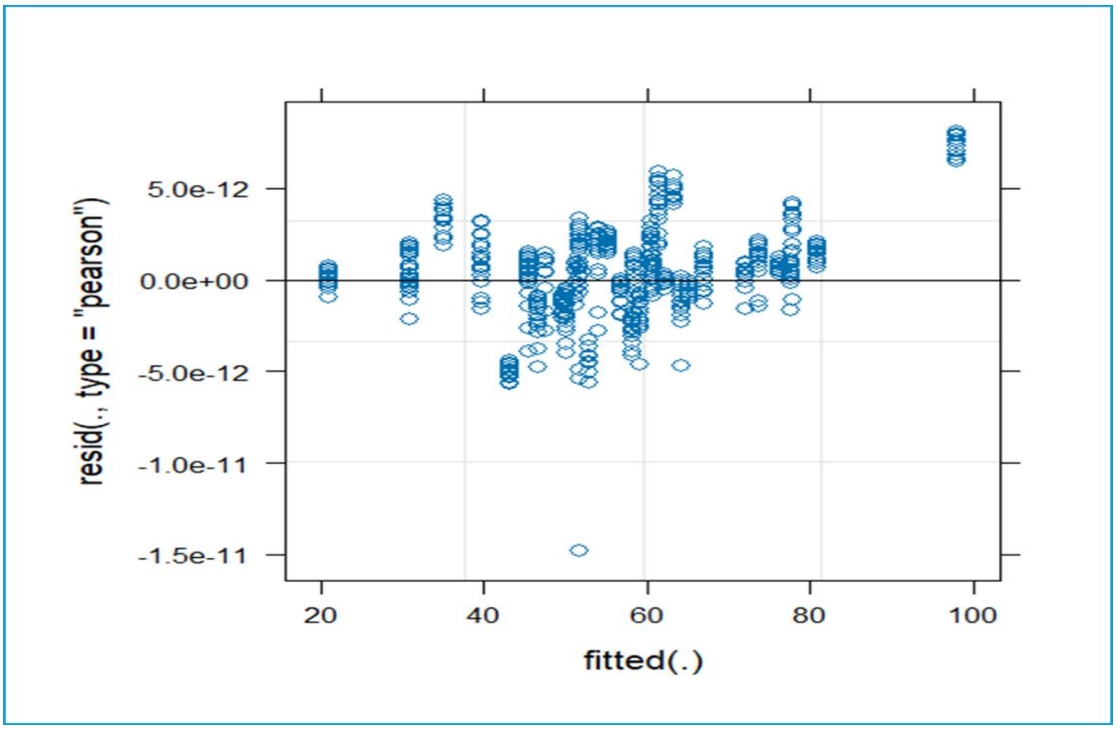


The model included state-level random intercepts, capturing unobserved heterogeneity across states. Some states showed positive deviations (e.g., states where NICS coverage was

consistently higher than predicted), while others showed negative deviations, indicating potential underperformance or data quality issues. This adjustment helps correct for systemic biases in RI or AFP data that vary geographically.

The model demonstrates that AFP surveillance indicators can be used to predict and adjust RI coverage estimates, aligning them more closely with NICS benchmarks. The inclusion of random effects by state improves accuracy by accounting for regional differences in reporting, infrastructure, or population dynamics. In the following section, the researcher checked the residual diagnosis of the predicted and the observed, as seen in Figure 24.

Figure 24:Residual diagnosis for Mixed-Effect



The residual plot from the mixed-effects model showed that Residuals were tightly clustered around zero, indicating minimal deviation between predicted and observed values. The points aligned closely along a straight line in the predicted vs. observed plot, suggesting a near-

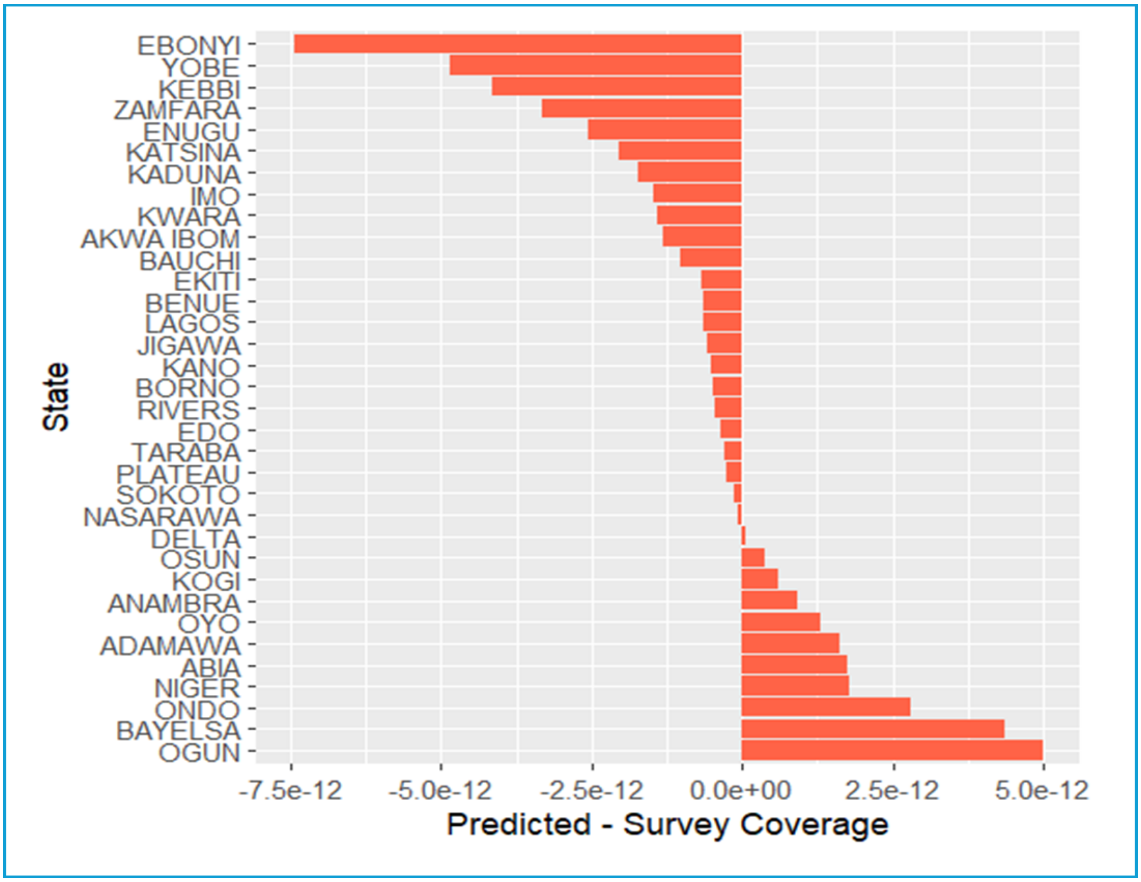
perfect fit. The relationship between predictors and the outcome appears linear, which supports the use of a linear model. There is no clear pattern or funnel shape in the residuals, indicating that the variance of errors is consistent across fitted values, which suggests Homoscedasticity. The residual diagnostics suggest that the model fits the data exceptionally well, with minimal error and no significant violations of assumptions. However, further validation using cross-validation or external data is recommended to ensure generalizability and guard against overfitting.

4.7.4. Measuring Intervention Impact

The model used in this study conducted a comprehensive analysis of immunisation interventions across different states. It aimed to determine the extent of coverage gaps by assessing vaccination rates before and after the implementation of specific activities. These activities included targeted immunisation campaigns, awareness drives, and logistical improvements.

The study utilized survey coverage data as the primary benchmark to measure the impact of these interventions. The results of this analysis are visually represented in Figures 25 and 26, which illustrate the changes in vaccination coverage levels over time and across regions, providing insights into the effectiveness of the interventions and identifying areas where further efforts are needed.

Figure 25: True Coverage Gap by States in Nigeria Adjusted by NICS Survey



From the predicted coverage gap using NICS OPV3 coverage, positive values mean the model predicted higher coverage than what was observed in the survey, while negative values mean the survey showed higher coverage than the model predicted.

EBONYI has the largest negative gap, meaning the survey found better coverage than expected. This could suggest:

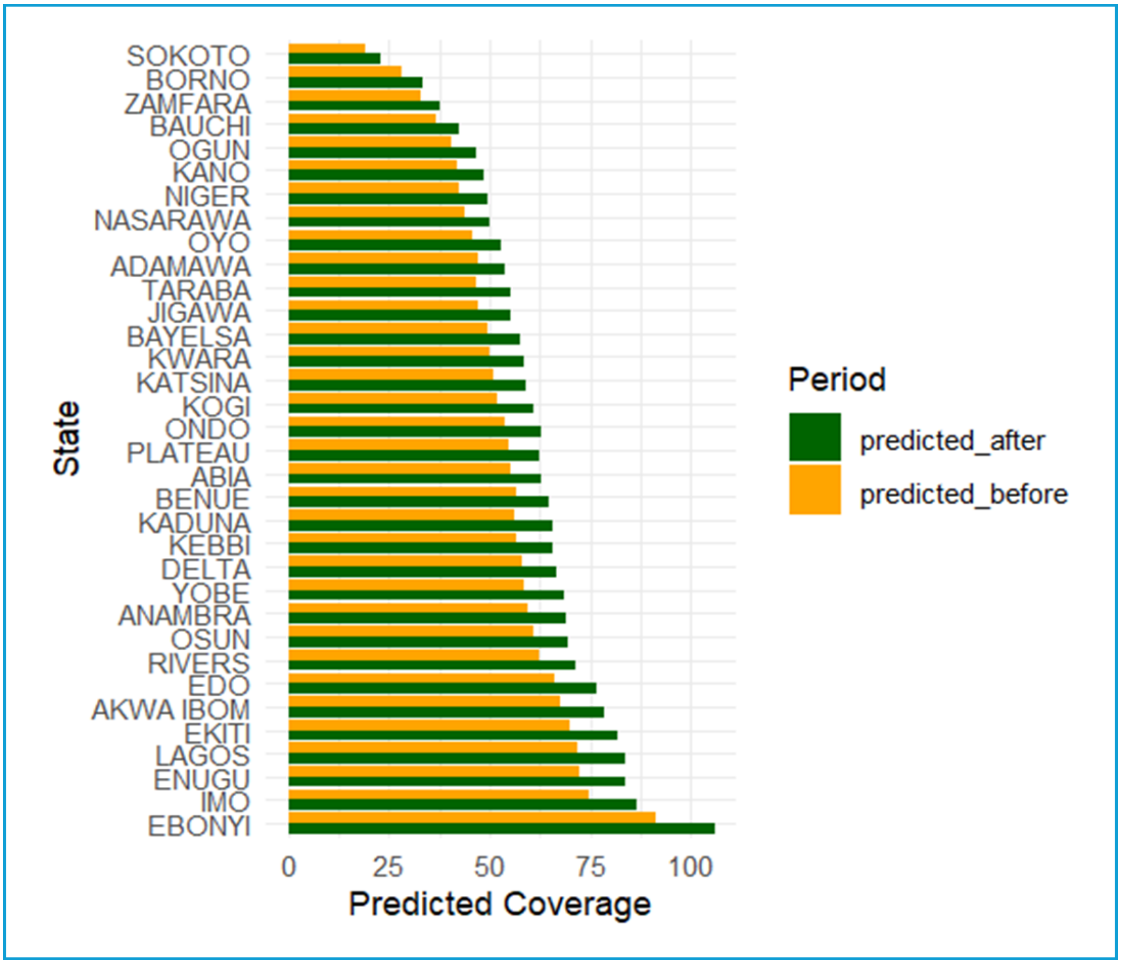
- The intervention was more effective than modeled.
- The model underestimated local efforts or population behavior.

OGUN has the largest positive gap, meaning the model predicted better coverage than what the survey found. This could indicate:

- The intervention didn't reach the expected population.
- There were implementation challenges or data quality issues.

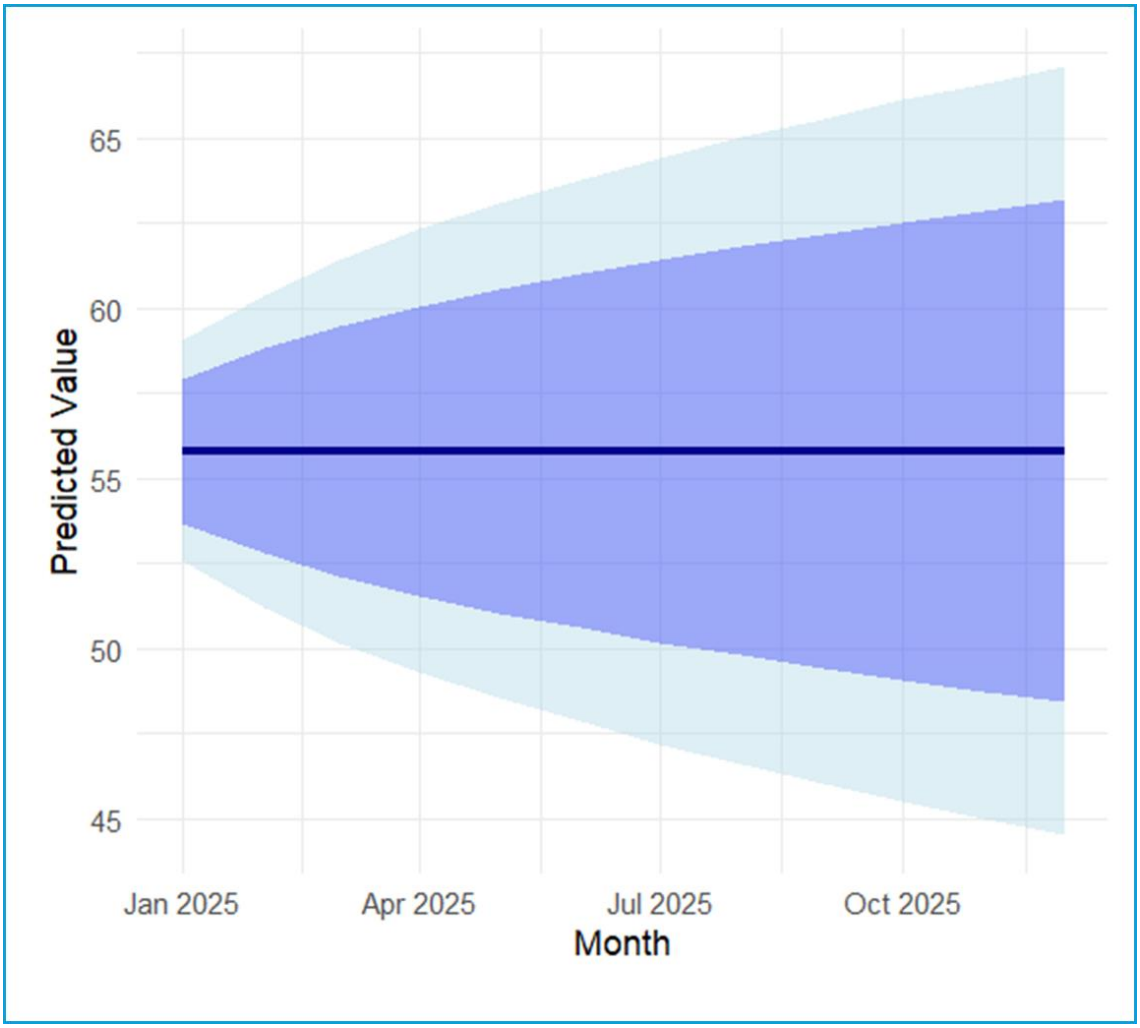
The range of values (from ~−7.5e−12 to ~5.0e−12) is minimal, possibly due to scaling or unit adjustments. The researcher further multiplies the gap by 100 to express it as a percentage difference for clearer interpretation, as seen in Figure 27.

Figure 26: Predicted Coverage, before and after Intervention



The model further utilises the OPV3 coverage from 2022 to 2024 to forecast the coverage for 2025 using the ARIMA model, as seen in Figure 28, adjusted by the NICS OPV3 2022 survey coverage.

Figure 27: ARIMA 2025 Nigeria immunisation coverage prediction Model



The ARIMA model is a time series forecasting method. It predicts the Nigerian 2025 immunisation values at 55 per cent across January to December based on patterns in past data, without explicitly knowing the real-world factors. Based on the 80 per cent (dark blue shade) and 95 per cent (light blue shade) confidence intervals, no strong upward or downward movement; the model expects coverage to hover around 55%. The prediction model can also be validated by NICS surveys that would be conducted. However, this study shows that AFP data can serve as a validation for immunisation true coverage. The following chapter discusses the summary, conclusion and recommendation of this thesis.

CHAPTER V: SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1. Introduction

Polio eradication remains a key and urgent global health priority. While substantial progress has been made in decreasing wild poliovirus cases, countries like Nigeria still face ongoing challenges in maintaining high immunisation rates and ensuring fair protection for all communities. A significant hurdle is the discrepancy between administrative coverage reports, household survey results, and actual immunisation rates, especially among children who have received no doses or missed doses. The existence of various data sources, such as Acute Flaccid Paralysis (AFP) surveillance, National Immunisation Coverage Surveys (NICS), and Routine Immunisation (RI) administrative data, offers a valuable opportunity to better analyse vaccination coverage patterns and disease risks at subnational levels.

This study is set within this context, aiming to integrate various data sources to predict polio burden, evaluate vaccination performance, and assess intervention effects across Nigerian states and Local Government Areas (LGAs). It combines AFP-derived coverage estimates, NICS survey results, and RI coverage data from 2022 to 2024. The goal is to identify factors contributing to immunisation gaps, highlight the burden of zero-dose children, and predict areas at higher risk for poliovirus transmission. By employing statistical models like random forest classification, linear regression, and mixed-effect models, the study develops a framework for predictive analytics to support targeted vaccination efforts.

This research is important for practical reasons: policymakers and immunisation program managers need reliable, evidence-based insights to allocate resources properly, identify high-risk regions, and create interventions to address immunity gaps. Additionally, by using thorough modelling on real-world surveillance and coverage data, this study shows how predictive methods

can enhance current monitoring systems in global health governance. Overall, it supports Nigeria's efforts to eliminate polio and provides a methodological framework that can be useful to other low- and middle-income countries facing similar issues.

5.2. Summary of the Study

This study analysed AFP surveillance data, NICS survey results, and RI coverage records from 2022 to 2024 to create a more reliable and predictive understanding of polio immunisation performance in Nigeria. The research objectives aimed to: (1) assess trends in routine immunisation coverage across states and LGAs, (2) explore the relationship between AFP-reported coverage, NICS estimates, and suspected AFP cases, and (3) build predictive models to identify high-burden LGAs and evaluate the effects of interventions.

Data from various sources were combined, cleaned, and harmonised to form a comprehensive dataset covering 774 LGAs. The analysis focused on RI coverage for OPV0–OPV3, surviving infant populations, AFP surveillance indicators, zero-dose data, and NICS estimates. This approach helped resolve discrepancies between administrative coverage and survey data by considering population denominators and surveillance effectiveness. Coverage patterns revealed significant subnational differences: some LGAs maintained consistently high (>90%) OPV3 coverage, while others showed ongoing gaps, often coinciding with high zero-dose areas.

Statistical analysis identified significant links between AFP OPV3 coverage and NICS OPV3 outcomes, indicating that AFP surveillance indicators can serve as predictors for community-level coverage. Nonetheless, inconsistencies appeared in states with poor surveillance or under-reporting, emphasising the limitations of relying on a single data source. Random forest classification showcased the potential of machine learning to categorise LGAs into low, medium,

and high burden groups, though the accuracy was affected by the training data balance. Additional analysis with linear regression and mixed-effect models revealed that AFP OPV3 was a consistently strong predictor of NICS OPV3, while AFP case numbers had only a minor impact on the variance explained.

The impact analysis of the intervention pinpointed the top 10 LGAs with the most significant increases in RI coverage from 2022 to 2024. These locations exhibited notable improvements in OPV0–OPV3 uptake, showcasing the success of targeted vaccination efforts. Nonetheless, a paired t-test comparing predicted results with actual outcomes showed statistically significant differences, suggesting that although the models reflected general trends, they underestimated local differences.

The study emphasises the need to combine various data sources for more precise immunization monitoring. While predictive modeling provides useful insights, it should be supported by local knowledge about surveillance quality and population changes. The findings help shape national polio eradication strategies by pinpointing priority LGAs, directing interventions, and addressing the ongoing issue of zero-dose children. Ultimately, this research enhances the evidence supporting targeted, data-driven immunization efforts across Nigeria.

5.3. Summary of Findings

This study aimed to integrate various data sources, AFP surveillance, NICS household surveys, and RI coverage records from 2022 to 2024, to analyse polio immunisation coverage and burdens at the subnational level in Nigeria. The results offered key insights into immunization performance, disparities among states and LGAs, and demonstrated how predictive models can help guide eradication efforts.

First, the trends in routine immunization (RI) coverage showed significant variation across the 774 LGAs analysed. Although some LGAs consistently reached over 90% coverage for OPV3, many others did not meet the national targets. This uneven coverage underscores ongoing challenges in ensuring equitable immunization services, especially in northern states, where higher suspected polio case reports and persistent coverage gaps remain common.

Second, the analysis showed strong correlations between AFP surveillance-based estimates of OPV3 coverage and the results from NICS surveys. Linear regression confirmed that AFP OPV3 coverage is a significant predictor of NICS OPV3 outcomes, accounting for a notable part of the variation. However, AFP case counts had only a weak association with NICS outcomes, indicating that although surveillance quality is crucial, case counts alone do not adequately predict immunisation coverage or risk levels.

Third, predictive modelling added further value by categorising LGAs according to their risk levels. The random forest analysis showed that indicators like RI coverage, zero-dose prevalence, and AFP data could jointly predict the burden status of LGAS. Nevertheless, the model's accuracy varied among categories: it was more precise in identifying low-burden LGAs than medium or high-burden ones. This highlights the need to balance datasets and enhance surveillance sensitivity to prevent underestimating risks in high-burden regions.

Fourth, the intervention impact analysis highlighted the top 10 LGAs with the most significant increases in RI coverage from 2022 to 2024. These LGAs saw notable rises in OPV0–OPV3 uptake, with coverage improvements frequently surpassing 20 percentage points. Importantly, these gains were not evenly spread across all states, indicating that tailored, localized strategies and context-specific interventions played a crucial role in driving success.

Lastly, a paired t-test comparing the predicted results and actual NICS data showed significant differences, although the mean estimates were closely aligned. This suggests that while predictive models effectively identify overall trends, they might underestimate specific local variations. Therefore, although models are valuable for guiding interventions, they should be supplemented with qualitative assessments of context, including factors like population mobility, vaccine hesitancy, and health system performance.

In summary, the findings highlight three main themes: (1) ongoing disparities in immunisation coverage at the subnational level, (2) the usefulness of AFP surveillance data for predicting NICS outcomes, and (3) the promise of integrated modelling methods to inform targeted interventions.

5.4. Conclusions

This thesis enhances the understanding of polio immunisation trends in Nigeria by combining various datasets to analyse coverage, pinpoint gaps, and evaluate the effects of interventions. It shows that, although Nigeria has made notable advances in increasing immunisation coverage, ongoing disparities persist, particularly in northern states where zero-dose prevalence is high and surveillance data frequently differs from survey results.

The study finds that AFP surveillance indicators, especially OPV3 coverage estimates, are strong predictors of NICS outcomes and can reliably stand in for immunisation performance when survey data is missing. However, using AFP case counts alone is inadequate because they vary greatly and depend on surveillance sensitivity. Predictive models like random forest and linear mixed-effects models are useful for classifying LGAs into risk groups and predicting coverage trends. Still, these models work best for identifying low-burden LGAs and are less accurate for

high-burden areas, highlighting the need to improve data quality and ensure balanced training datasets.

The intervention analysis shows that significant improvements are possible through targeted strategies. The best-performing LGAs proved that localized efforts, like intensified outreach, enhanced microplanning, and better resource allocation, can quickly boost vaccine uptake. Nonetheless, the uneven distribution of these gains highlights the importance of ongoing and equitable efforts to prevent any LGA from lagging behind.

Overall, the thesis concludes that predictive analytics can enhance existing monitoring frameworks by offering forward-looking insights into immunisation performance and aiding resource allocation. However, predictive models should serve as a complement to traditional surveillance and survey systems, not a replacement. The findings highlight that data triangulation, integrating AFP, NICS, RI, zero-dose indicators, and interventions conducted at sub-national levels, is crucial for obtaining a clearer understanding of immunisation coverage and polio risk.

This study, by combining various data sources and employing rigorous modelling, offers a practical framework for evidence-based decision-making in Nigeria's polio eradication efforts. Its insights are relevant beyond Nigeria, providing useful lessons for other low- and middle-income countries facing issues like incomplete data, unequal coverage, and the necessity for targeted strategies to meet eradication objectives.

5.5. Recommendations

Based on the findings, the following recommendations are proposed:

1. Strengthen data integration and harmonisation: Nigeria should institutionalise frameworks that integrate AFP surveillance, NICS surveys, and RI coverage data at both national and subnational levels. A unified database would reduce inconsistencies and allow real-time monitoring of immunisation performance.
2. Prioritize tracking zero-dose children, especially in northern states. Use zero-dose prevalence as a key indicator for directing resources and planning interventions.
3. Enhance surveillance sensitivity: Although AFP OPV3 coverage reliably predicts NICS outcomes, differences remain because of variations in surveillance quality. Improving case detection and reporting systems will make predictive models more dependable.
4. Increase the application of predictive analytics: regularly integrate predictive models like random forests into program monitoring, and continuously improve them to better identify medium- and high-burden LGAs. Policymakers should also invest in developing local analytical skills for ongoing use.
5. Context-specific interventions: The top 10 LGAs showing the greatest intervention impact proved that tailored strategies work. Future efforts should focus on local solutions, tackling obstacles like population mobility, vaccine hesitancy, and health system gaps.
6. Policy and programmatic adoption: Findings from predictive models should directly guide micro plans and national immunisation strategies. Regularly sharing model results with policymakers and field teams will strengthen evidence-based actions.

These recommendations highlight the importance of both strengthening traditional surveillance and adopting innovative predictive tools. By doing so, Nigeria can speed up its progress towards polio eradication and establish a model that other countries can follow.

5.6. Suggestions for Further Study

While this study provides valuable insights, several areas warrant further research:

1. Longitudinal impact of interventions: Future studies should monitor the same LGAs over several years to determine if intervention gains are maintained. A longitudinal approach would offer deeper understanding of the longevity of coverage improvements.
2. Expanded modelling approaches: Although this thesis used random forests and mixed-effect models, additional methods such as Bayesian hierarchical models or spatio-temporal models could offer more nuanced predictions, especially for high-burden LGAs.
3. Future studies should include socio-demographic factors like maternal education, household wealth, urban–rural differences, and cultural practices. These variables may help explain differences in immunization rates that go beyond simple surveillance and coverage metrics.
4. Assessment of vaccine hesitancy: Qualitative studies are necessary to understand community-level barriers to vaccination. Merging predictive analytics with qualitative insights would offer a comprehensive understanding of zero-dose prevalence.
5. Health system resilience: Future research should examine how features of health systems, such as workforce distribution, cold chain performance, and financing, impact

immunisation coverage at the LGA level. Integrating health systems data with AFP/NICS/RI datasets would generate practical insights.

6. Geospatial analysis: Using satellite imagery, population mobility data, and geospatial mapping could improve predictions of high-risk LGAs. This approach would be especially helpful for identifying underserved settlements and mobile populations.
7. Comparative regional studies: Extending the analytical framework to other countries in sub-Saharan Africa would enable cross-country comparisons, enhance generalisability, and provide lessons for global eradication efforts.

In summary, future research should expand on this foundation by enlarging datasets, employing advanced modelling, and including socio-behavioural factors. This comprehensive approach will deepen understanding of immunisation performance and improve policymakers' ability to reach the last mile in polio eradication.

References

Abbott, S. L., Hamisu, A. W., Gidado, S., Etapelong, S. G., Edukugho, A. A., Hassan, I. A., Mawashi, K. Y., Bukbuk, D. N., Baba, M., Adekunle, A. J., Adamu, U. S., Damisa, E., Waziri, N. E., Archer, W. R., Franka, R., Wiesen, E., Braka, F., Bolu, O., Banda, R., & Shuaib, F. (2021). Enhancing acute flaccid paralysis surveillance system towards polio eradication: reverse cold chain monitoring in Nigeria, 2017 to 2019. *Pan Afr Med J*, *40*(Suppl 1), 7. https://doi.org/10.11604/pamj.supp.2021.40.1.27534

Abdallah, G., Msuya, H. M., Mtenga, S., Festo, C., Mhalu, G., Shabani, J., Tillya, R., Mwengee, W., Masanja, H., & Mkopi, A. (2024). Routine Immunization Status and Factors Associated with Immunization Coverage among Children Aged 12-23 Months in Tanzania. *Am J Trop Med Hyg*, *111*(6), 1356-1363. https://doi.org/10.4269/ajtmh.23-0563

Abdel-Fattah, A., El-Gilany, A. H., El-Masry, R., & Kanddeel, A. (2019). Acute flaccid paralysis in North East Delta, Egypt: A retrospective analysis of prospectively collected surveillance data. *J Infect Public Health*, *12*(5), 714-719. https://doi.org/10.1016/j.jiph.2019.03.016

Abrams, J. Y., Copeland, J. R., Tauxe, R. V., Date, K. A., Belay, E. D., Mody, R. K., & Mintz, E. D. (2013). Real-time modelling used for outbreak management during a cholera epidemic, Haiti, 2010-2011 [Article]. *Epidemiology and Infection*, *141*(6), 1276-1285. https://doi.org/10.1017/S0950268812001793

Adamu, A. A., Jalo, R. I., Ndwandwe, D., & Wiysonge, C. S. (2024). Informal health sector and routine immunization: making the case for harnessing the potentials of patent medicine vendors for the big catch-up to reduce zero-dose children in sub-Saharan Africa. *Front Public Health*, *12*, 1353902. https://doi.org/10.3389/fpubh.2024.1353902

Adesola, R. O., Idris, I., & Opuni, E. (2023). Public health concerns surrounding the cVDPV2 outbreak in Africa: Strategies for prevention and control with a special focus on Nigeria. *Health Science Reports*, *6*(5). https://doi.org/10.1002/hsr2.1269

Agócs, M., Ismail, A., Kamande, K., Tabu, C., Momanyi, C., Sale, G., Rhoda, D. A., Khamati, S., Mutonga, K., Mitto, B., & Hennessey, K. (2021). Reasons why children miss vaccinations in

Western Kenya; A step in a five-point plan to improve routine immunization. *Vaccine*, *39*(34), 4895-4902. https://doi.org/10.1016/j.vaccine.2021.02.071

Aheto, J. M. K., Olowe, I. D., Chan, H. M. T., Ekeh, A., Dieng, B., Fafunmi, B., Setayesh, H., Atuhaire, B., Crawford, J., Tatem, A. J., & Utazi, C. E. (2023). Geospatial Analyses of Recent Household Surveys to Assess Changes in the Distribution of Zero-Dose Children and Their Associated Factors before and during the COVID-19 Pandemic in Nigeria. *Vaccines (Basel)*, *11*(12). https://doi.org/10.3390/vaccines11121830

Ahmad, H., Sanef, S. A., Shahabudin, W. Z., Mohtar, N., Hassan, M. R., Jeffree, M. S., Lukman, K. A., Ghazi, H. F., & Syed Abdul Rahim, S. S. (2023). Socioecological Challenges of Polio Supplementary Immunization Activities (SIAs) in the Asia-Pacific Region: A Systematic Review. *J Environ Public Health*, *2023*, 4801424. https://doi.org/10.1155/2023/4801424

Ahonkhai, A. A., Odusanya, O. O., Meurice, F. P., Pierce, L. J., Durojaiye, T. O., Alufohai, E. F., Clemens, R., & Ahonkhai, V. I. (2022). Lessons for strengthening childhood immunization in low- and middle-income countries from a successful public-private partnership in rural Nigeria. *International Health*, *14*(6), 632-638. https://doi.org/10.1093/inthealth/ihab089

Alegana, V. A., Ticha, J. M., Mwenda, J. M., Katsande, R., Gacic-Dobo, M., Danovaro-Holliday, M. C., Shey, C. W., Akpaka, K. A., Kazembe, L. N., & Impouma, B. (2024). Modelling the spatial variability and uncertainty for under-vaccination and zero-dose children in fragile settings. *Sci Rep*, *14*(1), 24405. https://doi.org/10.1038/s41598-024-74982-5

Ali, A., Allzain, H., Ahmed, O. M., Mahgoub, E., Bashir, M. B. M., & Gorish, B. M. T. (2023). Evaluation of acute flaccid paralysis surveillance system in the River Nile State - Northern Sudan, 2021. *BMC Public Health*, *23*(1), 125. https://doi.org/10.1186/s12889-023-15019-w

Alkorashy, H. A., & Al-Hothaly, W. A. (2022). Quality of nursing care in Saudi's healthcare transformation era: A nursing perspective. *Int J Health Plann Manage*, *37*(3), 1566-1582. https://doi.org/10.1002/hpm.3425

Alleman, M. M., Jorba, J., Riziki, Y., Henderson, E., Mwehu, A., Seakamela, L., Howard, W., Kadiobo Mbule, A., Nsamba, R. N., Djawe, K., Yapi, M. D., Mengouo, M. N., Gumede, N., Ndoutabe,

M., Kfutwah, A. K. W., Senouci, K., & Burns, C. C. (2023). Vaccine-derived poliovirus serotype 2 outbreaks and response in the Democratic Republic of the Congo, 2017-2021. *Vaccine*, *41 Suppl 1*(Suppl 1), A35-a47. https://doi.org/10.1016/j.vaccine.2023.02.042

Amodan, B. O., Kisakye, A., Okumu, P. T., Ahirirwe, S. R., Kadobera, D., Driwale, A., & Ario, A. R. (2022). Trends of key surveillance performance indicators of acute flaccid paralysis: a descriptive analysis, Uganda, 2015-2020. *BMC Public Health*, *22*(1), 1694. https://doi.org/10.1186/s12889-022-14077-w

Angessa, R., Siliota, R., Anga, J., Kofela, T., Tanevska, S., Bainvalu, N., McNeil, P., & Sobel, H. L. (2024). Increasing immunization coverage, Solomon Islands, 2022. *Bull World Health Organ*, *102*(10), 736-741. https://doi.org/10.2471/blt.24.291084

Apeng, D., Drorit, D., Mabong, P., Theo, L., Fitzwarryne, C., & Bunat, A. (2010). The 'Reach Every Village' strategy for community-based health improvement interventions in the Momase Region of Papua New Guinea. *P N G Med J*, *53*(1-2), 37-47.

Arambepola, R., Yang, Y., Hutchinson, K., Mwansa, F. D., Doherty, J. A., Bwalya, F., Ndubani, P., Musukwa, G., Moss, W. J., Wesolowski, A., & Mutembo, S. (2021). Using geospatial models to map zero-dose children: factors associated with zero-dose vaccination status before and after a mass measles and rubella vaccination campaign in Southern province, Zambia. *BMJ Glob Health*, *6*(12). https://doi.org/10.1136/bmjgh-2021-007479

Basu, S., Ashok, G., Debroy, R., Ramaiah, S., Livingstone, P., & Anbarasu, A. (2023). Impact of the COVID-19 pandemic on routine vaccine landscape: A global perspective. *Hum Vaccin Immunother*, *19*(1), 2199656. https://doi.org/10.1080/21645515.2023.2199656

Bawa, S., McNab, C., Nkwogu, L., Braka, F., Obinya, E., Galway, M., Mirelman, A. J., Hammanyero, K. I., Safiyanu, G., Chukwuji, M., Ongwae, K., Mkanda, P., Corkum, M., Hegg, L., Tollefson, D., Umar, S., Audu, S., Gunda, H., Chinta, M.,...Shuaib, F. (2019). Using the polio programme to deliver primary health care in Nigeria: implementation research. *Bull World Health Organ*, *97*(1), 24-32. https://doi.org/10.2471/blt.18.211565

Bawa, S., Shuaib, F., Saidu, M., Ningi, A., Abdullahi, S., Abba, B., Idowu, A., Alkasim, J., Hammanyero, K., Warigon, C., Tegegne, S. G., Banda, R., Korir, C., Yehualashet, Y. G., Bedada, T., Martin, C., Nsubuga, P., Adamu, U. S., Okposen, B.,...Vaz, R. G. (2018). Conduct of vaccination in hard-to-reach areas to address potential polio reservoir areas, 2014-2015. *BMC Public Health*, *18*(Suppl 4), 1312. https://doi.org/10.1186/s12889-018-6194-y

Bellizzi, S., Pichierri, G., Kheirallah, K., & Panu Napodano, C. M. (2022). Global Health priorities: repositioning routine immunization for infants. *J Infect Dev Ctries*, *16*(10), 1648-1649. https://doi.org/10.3855/jidc.17165

Bessing, B., Dagoe, E. A., Tembo, D., Mwangombe, A., Kanyanga, M. K., Manneh, F., Matapo, B. B., Bobo, P. M., Chipoya, M., Eboh, V. A., Kayeye, P. L., Masumbu, P. K., Muzongwe, C., Bakyaita, N. N., Zomahoun, D., & Tuma, J. N. (2023). Evaluation of the Acute flaccid paralysis surveillance indicators in Zambia from 2015-2021: a retrospective analysis. *BMC Public Health*, *23*(1), 2227. https://doi.org/10.1186/s12889-023-17141-1

Biru, G., Gemechu, H., Gebremeskel, E., Nemomssa, H. D., Dese, K., Wakjira, E., Demlew, G., Yohannes, D., Abdi, K. L., Murad, H., Zewde, E. T., Habtamu, B., Tefera, M., Alayu, M., Gidi, N. W., Bisrat, F., Tadesse, T., Kidanne, L., Choe, S. W.,...Ayana, G. (2025). Community-Based Surveillance of Acute Flaccid Paralysis: A Review on Detection and Reporting Strategy. *J Epidemiol Glob Health*, *15*(1), 29. https://doi.org/10.1007/s44197-025-00349-2

Bogale, B., Tiruneh, G. T., Belete, N., Hunegnaw, B. M., Fesseha, N., Zergaw, T. S., Tadesse, H., Yeshiwas, T., Meseret, H., & Emaway, D. (2025). Risk factors associated with zero-dose and under-immunized children, and the number of vaccination doses received by children in Ethiopia: a negative binomial regression analysis. *BMC Public Health*, *25*(1), 1693. https://doi.org/10.1186/s12889-025-22837-7

Cherian, T., & Mantel, C. (2020). National immunization programmes. *Bundesgesundheitsblatt Gesundheitsforschung Gesundheitsschutz*, *63*(1), 16-24. https://doi.org/10.1007/s00103-019-03062-1 (Nationale Impfprogramme.)

Ciapponi, A., Bardach, A., Rey Ares, L., Glujovsky, D., Cafferata, M. L., Cesaroni, S., & Bhatti, A. (2019). Sequential inactivated (IPV) and live oral (OPV) poliovirus vaccines for preventing

poliomyelitis. *Cochrane Database Syst Rev*, *12*(12), Cd011260. https://doi.org/10.1002/14651858.CD011260.pub2

Dadari, I., Sharkey, A., Hoare, I., & Izurieta, R. (2023). Analysis of the impact of COVID-19 pandemic and response on routine childhood vaccination coverage and equity in Northern Nigeria: a mixed methods study. *BMJ Open*, *13*(10), e076154. https://doi.org/10.1136/bmjopen-2023-076154

Daley, M. F., Clarke, C. L., Glanz, J. M., Albers, A. N., Michels, S. Y., Freeman, R. E., & Newcomer, S. R. (2024). National trends in patterns of under-vaccination in early childhood: National Immunization Survey-Child, United States, 2011-2021. *Expert Rev Vaccines*, *23*(1), 740-749. https://doi.org/10.1080/14760584.2024.2389922

Doshmangir, L., Sanadghol, A., Kakemam, E., & Majdzadeh, R. (2025). The involvement of non-governmental organisations in achieving health system goals based on the WHO six building blocks: A scoping review on global evidence. *PLoS One*, *20*(1), e0315592. https://doi.org/10.1371/journal.pone.0315592

Dowdle, W. R., Featherstone, D. A., Birmingham, M. E., Hull, H. F., & Aylward, R. B. (1999). Poliomyelitis eradication. *Virus Res*, *62*(2), 185-192. https://doi.org/10.1016/s0168-1702(99)00044-1

Dunkle, S. E., Wallace, A. S., MacNeil, A., Mustafa, M., Gasasira, A., Ali, D., Elmousaad, H., Mahoney, F., & Sandhu, H. S. (2014). Limitations of using administratively reported immunization data for monitoring routine immunization system performance in Nigeria. *J Infect Dis*, *210 Suppl 1*(Suppl 1), S523-530. https://doi.org/10.1093/infdis/jiu373

Eales, O., McCaw, J. M., & Shearer, F. M. (2024). Challenges in the case-based surveillance of infectious diseases. *Royal Society Open Science*, *11*(8). https://doi.org/10.1098/rsos.240202

Endegue-Zanga, M. C., Sadeuh-Mba, S. A., Iber, J., Burns, C., Nimpa-Mengouo, M., Demanou, M., Vernet, G., Etoa, F. X., & Njouom, R. (2015). Circulating vaccine-derived polioviruses in the

Extreme North region of Cameroon. *J Clin Virol*, *62*, 80-83. https://doi.org/10.1016/j.jcv.2014.11.027

Etamesor, S., Ottih, C., Salihu, I. N., & Okpani, A. I. (2018). Data for decision making: using a dashboard to strengthen routine immunisation in Nigeria. *BMJ Glob Health*, *3*(5), e000807. https://doi.org/10.1136/bmjgh-2018-000807

Etsano, A., Damisa, E., Shuaib, F., Nganda, G. W., Enemaku, O., Usman, S., Adeniji, A., Jorba, J., Iber, J., Ohuabunwo, C., Nnadi, C., & Wiesen, E. (2016). Environmental Isolation of Circulating Vaccine-Derived Poliovirus After Interruption of Wild Poliovirus Transmission - Nigeria, 2016. *MMWR Morb Mortal Wkly Rep*, *65*(30), 770-773. https://doi.org/10.15585/mmwr.mm6530a4

Fernandez-Garcia, M. D., Majumdar, M., Kebe, O., Fall, A. D., Kone, M., Kande, M., Dabo, M., Sylla, M. S., Sompare, D., Howard, W., Faye, O., Martin, J., & Ndiaye, K. (2018). Emergence of Vaccine-Derived Polioviruses during Ebola Virus Disease Outbreak, Guinea, 2014-2015. *Emerg Infect Dis*, *24*(1), 65-74. https://doi.org/10.3201/eid2401.171174

GAVI. (2022). *ZIP: a new way to get vaccines to zero-dose children in some of the world's toughest regions*. https://www.gavi.org/vaccineswork/zip-new-way-get-vaccines-zero-dose-children-some-worlds-toughest-regions

GAVI. (2023). Media Fact Sheet: Takeaways from the 2022 WUENIC estimates for 57 lower-income countries supported by Gavi

Gebremedhin, S., Shiferie, F., Tsegaye, D. A., Alemayehu, W. A., Wondie, T., Donofrio, J., DelPizzo, F., Belete, K., & Biks, G. A. (2023). Oral and Inactivated Polio Vaccine Coverage and Determinants of Coverage Inequality Among the Most At-Risk Populations in Ethiopia. *Am J Trop Med Hyg*, *109*(5), 1148-1156. https://doi.org/10.4269/ajtmh.23-0319

GPEI. (2023). *Global-AFP-guidelines-pre-publiucation-version-2023.pdf*.

GPEI. (2025). Surveillance Indicators. https://polioeradication.org/what-we-do/surveillance-indicators/

Gulumbe, B. H., Danlami, M. B., Yusuf, A. B., Shehu, A., & Chidiebere, O. (2024). Vaccine hesitancy under the lens: Nigeria's struggle against the worst diphtheria outbreak in decades. *Ther Adv Infect Dis*, *11*, 20499361241242218. https://doi.org/10.1177/20499361241242218

Hamisu, A. W., Shuaib, F., Johnson, T. M., Craig, K., Fiona, B., Banda, R., Tegegne, S. G., Oyetunji, A., Erbeto, T. B., Nsubuga, P., Vaz, R. G., Muhamed, A. J. G., & Usman, A. (2018). Profile of polio-compatible cases in Nigeria, 2006-2016. *BMC Public Health*, *18*(Suppl 4), 1308. https://doi.org/10.1186/s12889-018-6184-0

Harrison, K., Rahimi, N., & Danovaro-Holliday, M. C. (2020). Factors limiting data quality in the expanded programme on immunization in low and middle-income countries: A scoping review. *Vaccine*, *38*(30), 4652-4663. https://doi.org/10.1016/j.vaccine.2020.02.091

Hoffman, L., & Walters, R. W. (2022). Catching Up on Multilevel Modeling. *Annu Rev Psychol*, *73*, 659-689. https://doi.org/10.1146/annurev-psych-020821-103525

IA2030. (2024). *IMMUNIZATION AGENDA 2030 GLOBAL REPORT 2021: Advancing the Immunization Agenda 2030 during the COVID-19 pandemic*. https://geneva.usmission.gov/2021/05/28/us-canada-joint-statement-on-immunization-agenda-2030

Idris, I. O., Tapkigen, J., Kabutaulaka, G., Ayeni, G. O., Ayomoh, F. I., & Obwoya, J. G. (2022). Are children on track with their routine immunization schedule in a fragile and protracted conflict state of South Sudan? A community-based cross-sectional study. *BMC Pediatr*, *22*(1), 147. https://doi.org/10.1186/s12887-022-03213-5

Ishoso, D. K., Mafuta, E., Danovaro-Holliday, M. C., Ngandu, C., Menning, L., Cikomola, A. M., Lungayo, C. L., Mukendi, J. C., Mwamba, D., Mboussou, F. F., Manirakiza, D., Yapi, M. D., Ngabo, G. F., Riziki, R. B., Aluma, A. D. L., Tsobeng, B. N., Mwanga, C., Otomba, J., Lulebo, A.,...Nimpa, M. M. (2023). Reasons for Being "Zero-Dose and Under-Vaccinated" among Children Aged 12-23 Months in the Democratic Republic of the Congo. *Vaccines (Basel)*, *11*(8). https://doi.org/10.3390/vaccines11081370

Jaramillo, J., Ning, M. F., Cadena, L., Park, M., Lo, T., Zielinski-Gutierrez, E., Espinosa-Bode, A., Reyes, M., Del Rosario Polo, M., & Henao, O. (2022). Evaluation of the collaborative

integrated surveillance system (ViCo) in Guatemala: a qualitative study on lessons learned and future perspectives. *BMC Public Health*, *22*(1), 350. https://doi.org/10.1186/s12889-022-12719-7

Jean Baptiste, A. E., Bawa, S., Oteri, A. J., Dieng, B., Shuaib, F., & Mulombo, W. K. (2021). Nationwide measles supplementary immunization activities to increase immunity levels in Nigeria. *Vaccine*, *39 Suppl 3*, C1-c2. https://doi.org/10.1016/j.vaccine.2021.08.084

Jenkins, H. E., Aylward, R. B., Gasasira, A., Donnelly, C. A., Mwanza, M., Corander, J., Garnier, S., Chauvin, C., Abanida, E., Pate, M. A., Adu, F., Baba, M., & Grassly, N. C. (2010). Implications of a circulating vaccine-derived poliovirus in Nigeria. *N Engl J Med*, *362*(25), 2360-2369. https://doi.org/10.1056/NEJMoa0910074

Jiee, S. F., Bondi, M. E., Emiral, M. E., & Jantim, A. (2021). Polio Supplementary Immunization Activities During COVID-19 Pandemic: Experience from Penampang District, Sabah, Malaysia. *J Prim Care Community Health*, *12*, 21501327211029800. https://doi.org/10.1177/21501327211029800

Jil, J. M., Tegegne, A. A., Maleghemi, S., Berta, K. K., Birru, T. G., & Kilo, O. T. D. (2022). Acute flaccid paralysis surveillance performance from 2011 to 2020 in Jonglei State, South Sudan: progress and challenges encountered. *Pan Afr Med J*, *42*(Suppl 1), 11. https://doi.org/10.11604/pamj.supp.2022.42.1.33966

Kanyuuru, L., Kabue, M., Ashengo, T. A., Ruparelia, C., Mokaya, E., & Malonza, I. (2015). RED for PMTCT: an adaptation of immunization's Reaching Every District approach increases coverage, access, and utilization of PMTCT care in Bondo District, Kenya. *Int J Gynaecol Obstet*, *130 Suppl 2*, S68-73. https://doi.org/10.1016/j.ijgo.2015.04.002

Korukluoglu, G., Ozdemirer, U., Bayrakdar, F., Unal, Z., Cosgun, Y., Atak, T., Karademirtok, H., Ata, I., & Kara, F. (2021). Detection of non-polio and polio enteroviruses in Acute Flaccid Paralysis surveillance in Turkey. *Acta Microbiol Immunol Hung*, *68*(2), 92-98. https://doi.org/10.1556/030.2021.01353

Levin, K. A. (2006). Study design III: Cross-sectional studies. *Evid Based Dent*, *7*(1), 24-25. https://doi.org/10.1038/sj.ebd.6400375

London, I. C. (2025). *Health System Development Summative*.

Lorenzetti, L., Haydarov, R., Namey, E., Lawton, A., Nam, H., Ridwan Hasan, M., Monj, C., Abeyesekera, S., Amina Kabwau, M., & McIntosh, R. (2023). Exploring public perceptions of vaccine-derived poliovirus and a novel oral polio vaccine in the Democratic Republic of the Congo, Kenya, and Nigeria. *Vaccine*, *41 Suppl 1*, A128-a135. https://doi.org/10.1016/j.vaccine.2022.05.020

Lukwago, L., Nanyunja, M., Ndayimirije, N., Wamala, J., Malimbo, M., Mbabazi, W., Gasasira, A., Nabukenya, I. N., Musenero, M., Alemu, W., Perry, H., Nsubuga, P., & Talisuna, A. (2013). The implementation of Integrated Disease Surveillance and Response in Uganda: a review of progress and challenges between 2001 and 2007. *Health Policy and Planning*, *28*(1), 30-40. https://doi.org/https://dx.doi.org/10.1093/heapol/czs022

Maleghemi, S., Tegegne, A. A., Ferede, M., Bassey, B. E., Akpan, G. U., Bello, I. M., Ticha, J. M., Anyuon, A., Waya, J. L., Okiror, S. O., Ndoutabe, M., Berta, K. K., Ndenzako, F., Mkanda, P., & Olu, O. O. (2022). Polio eradication in a chronic conflict setting lessons from the Republic of South Sudan, 2010-2020. *Pan Afr Med J*, *42*(Suppl 1), 3. https://doi.org/10.11604/pamj.supp.2022.42.1.32922

Matthew, A. A., Motunrayo, I. F., Rejoice, U. O., Gideon, I. N., & Henry, U. U. (2024). Factors associated with full childhood vaccination coverage among young mothers in Northern Nigeria.pdf. https://www.panafrican-med-journal.com/content/article/47/4/pdf/4.pdf

Mbaeyi, C., Moran, T., Wadood, Z., Ather, F., Sykes, E., Nikulin, J., Al Safadi, M., Stehling-Ariza, T., Zomahoun, L., Ismaili, A., Abourshaid, N., Asghar, H., Korukluoglu, G., Duizer, E., Ehrhardt, D., Burns, C. C., & Sharaf, M. (2021). Stopping a polio outbreak in the midst of war: Lessons from Syria. *Vaccine*, *39*(28), 3717-3723. https://doi.org/10.1016/j.vaccine.2021.05.045

Mellis, C. M. (2020). How to choose your study design. *J Paediatr Child Health*, *56*(7), 1018-1022. https://doi.org/10.1111/jpc.14929

Morais, A., Morais, J., Felix, M., Neto, Z., Madaleno, V., Umar, A. S., Panda, N., Lemma, F., Chivale, J. A. L., Cavalcante, D. G., Davlantes, E., Ghiselli, M., Espinosa, C., Whiteman, A., Iber, J., Henderson, E., Bullard, K., Jorba, J., Burns, C. C.,...Frawley, A. (2023). Genetic and epidemiological description of an outbreak of circulating vaccine-derived polio-virus type 2 (cVDPV2) in Angola, 2019-2020. *Vaccine*, *41 Suppl 1*(Suppl 1), A48-a57. https://doi.org/10.1016/j.vaccine.2023.02.035

Mustafa, U.-K., Sauli, E., Kreppel, K. S., Boenecke, J., & Brinkel, J. (2025). Evaluation of the acceptability of ESIDA app, a smartphone-based clinical decision support application to improve infectious disease outbreak detection in Tanzania: clinician perspectives. *BMC Public Health*, *25*(1), 2197. https://doi.org/https://dx.doi.org/10.1186/s12889-025-23286-y

NBS, NPHCDA, BMGF, GAVI, & UNICEF. (2022). *NIGERIA 2021 MULTIPLE INDICATOR CLUSTER SURVEY (MICS) &*

NATIONAL IMMUNIZATION COVERAGE SURVEY (NICS).

Odoom, J. K., Dzotse, E. K., Nii-Trebi, N. I., Opare, D., Akyereko, E., Attiku, K., Duker, E. O., Eshun, M., Boahene, B. B., Gberbi, E., Houphouet, E. E., Diamenu, S., Adjabeng, M., Asamoah-Frimpong, J., Ameme, D., Opare, J. K. L., & Obodai, E. (2024). Outbreak Response to Circulating Vaccine-Derived Poliovirus in Three Northern Regions of Ghana, 2019. *Biomed Res Int*, *2024*, 5515777. https://doi.org/10.1155/2024/5515777

Odoom, J. K., Obodai, E., Boateng, G., Diamenu, S., Attiku, K., Avevor, P., Duker, E., Boahene, B., Eshun, M., Gberbie, E., & Opare, J. K. L. (2021). Detection of vaccine-derived poliovirus circulation by environmental surveillance in the absence of clinical cases. *Hum Vaccin Immunother*, *17*(7), 2117-2124. https://doi.org/10.1080/21645515.2020.1852009

Ogbuabor, D. C., Ghasi, N., Okenwa, U. J., Nwangwu, C. N., Ezenwaka, U., & Onwujekwe, O. (2022). Assessing the quality of immunization data from administrative data in Enugu State, South-East Nigeria: A cross-sectional study. *Niger J Clin Pract*, *25*(11), 1864-1874. https://doi.org/10.4103/njcp.njcp_291_22

Ohta, A., Murakami, Y., Hashimoto, S., Nagai, M., Kawado, M., Izumida, M., Tada, Y., Shigematsu, M., Yasui, Y., & Taniguchi, K. (2007). Epidemics of influenza and pediatric diseases observed in infectious disease surveillance in Japan, 1999-2005. *Journal of epidemiology*, *17 Suppl*(cl8, 9607688), S14-22. https://doi.org/https://dx.doi.org/10.2188/jea.17.s14

Omoleke, S. A., Omotara, B. A., Oyeyemi, A. L., Beida, O., & Etatuvie, S. O. (2023). Immunisation services in North-Eastern Nigeria: Perspectives of critical stakeholders to improve uptake and service delivery. *J Public Health Afr*, *14*(11), 1807. https://doi.org/10.4081/jphia.2023.1807

Oot, L., Adam, Z., Alemayehu, T., Almiñana, A., Dagnew, B., Girma, D., Herrera, E., Kanagat, N., & Rogers-Bloch, Q. (2023). Applying quality improvement tools to the Reaching Every District strategy: a mixed-methods examination of a systems strengthening approach to building the capacity of immunization managers and service providers in Ethiopia. *Pan Afr Med J*, *44*, 180. https://doi.org/10.11604/pamj.2023.44.180.35810

Rosewell, A., Spokes, P. J., & Gilmour, R. E. (2012). NSW Annual vaccine-preventable disease report, 2011. *N S W Public Health Bull*, *23*(9-10), 171-178. https://doi.org/10.1071/nb12086

Sabahelzain, M. M., Dwyer, H., Abimbola, S., & Leask, J. (2025). Implications of conflict on vaccination in the Sahel region. *BMJ Glob Health*, *10*(1). https://doi.org/10.1136/bmjgh-2024-016496

Sato, R. (2023). Zero-Dose, Under-Immunized, and Dropout Children in Nigeria: The Trend and Its Contributing Factors over Time. *Vaccines (Basel)*, *11*(1). https://doi.org/10.3390/vaccines11010181

Sato, R., Thompson, A., Sani, I., Metiboba, L., Giwa, A., Femi-Ojo, O., & Odezugo, V. (2021). Effect of Vaccine Direct Delivery (VDD) on vaccine stockouts and number of vaccinations: Case study from Bauchi State, Nigeria. *Vaccine*, *39*(9), 1445-1451. https://doi.org/10.1016/j.vaccine.2021.01.037

Sato, R., & Titus, T. (2021). Effect of tailored information of vaccination schedule on vaccine uptake in northern Nigeria. *Hum Vaccin Immunother*, *17*(10), 3818-3822. https://doi.org/10.1080/21645515.2021.1936861

Savitz, D. A., & Wellenius, G. A. (2023). Can Cross-Sectional Studies Contribute to Causal Inference? It Depends. *Am J Epidemiol*, *192*(4), 514-516. https://doi.org/10.1093/aje/kwac037

Scobie, H. M., Edelstein, M., Nicol, E., Morice, A., Rahimi, N., MacDonald, N. E., Danovaro-Holliday, C. M., Jawad, J., Immunization, S. W. G. o., Surveillance Data, Q., & Use. (2020). Improving the quality and use of immunization and surveillance data: Summary report of the Working Group of the Strategic Advisory Group of Experts on Immunization. *Vaccine*, *38*(46), 7183-7197. https://doi.org/10.1016/j.vaccine.2020.09.017

Shattock, A. J., Johnson, H. C., Sim, S. Y., Carter, A., Lambach, P., Hutubessy, R. C. W., Thompson, K. M., Badizadegan, K., Lambert, B., Ferrari, M. J., Jit, M., Fu, H., Silal, S. P., Hounsell, R. A., White, R. G., Mosser, J. F., Gaythorpe, K. A. M., Trotter, C. L., Lindstrand, A.,...Bar-Zeev, N. (2024). Contribution of vaccination to improved survival and health: modelling 50 years of the Expanded Programme on Immunization. *Lancet*, *403*(10441), 2307-2316. https://doi.org/10.1016/s0140-6736(24)00850-x

Shuaib, F., Garba, A. B., Meribole, E., Obasi, S., Sule, A., Nnadi, C., Waziri, N. E., Bolu, O., Nguku, P. M., Ghiselli, M., Adegoke, O. J., Jacenko, S., Mungure, E., Gidado, S., Wilson, I., Wiesen, E., Elmousaad, H., Bloland, P., Rosencrans, L.,...Vertefeuille, J. (2020). Implementing the routine immunisation data module and dashboard of DHIS2 in Nigeria, 2014–2019. *BMJ Global Health*, *5*(7), e002203. https://doi.org/10.1136/bmjgh-2019-002203

Shuaib, F. M. B., Musa, P. F., Gashu, S. T., Onoka, C., Ahmed, S. A., Bagana, M., Galway, M., Braka, F., Muluh, T. J., Banda, R., Akpan, G., Tunji, A., Idris, U. K., Olusoga, A., Briand, P., Obiako, N., Nebechukwu, T., & Mkanda, P. (2018). AVADAR (Auto-Visual AFP Detection and Reporting): demonstration of a novel SMS-based smartphone application to improve acute flaccid paralysis (AFP) surveillance in Nigeria. *BMC Public Health*, *18*(Suppl 4), 1305. https://doi.org/10.1186/s12889-018-6187-x

Tefera, B. B., Kibret, M. A., Molla, Y. B., Kassie, G., Hailemichael, A., Abate, T., Zelelew, H., Desta, B. F., Futrell, E., Kebede, Z., Abelti, G., Routh, S., Feyisetan, B., & Saad, A. (2021). The interaction of healthcare service quality and community-based health insurance in Ethiopia. *PLoS One*, *16*(8), e0256132. https://doi.org/10.1371/journal.pone.0256132

Tossaint-Schoenmakers, R., Versluis, A., Chavannes, N., Talboom-Kamp, E., & Kasteleyn, M. (2021). The Challenge of Integrating eHealth Into Health Care: Systematic Literature Review of the Donabedian Model of Structure, Process, and Outcome. *J Med Internet Res*, *23*(5), e27180. https://doi.org/10.2196/27180

Umutesi, G., Moon, T. D., Makam, J. K., Diomande, F., Cherry, C. B., Tuopileyi Ii, R. N., Zakari, W., & Craig, A. S. (2023). Evaluation of acute flaccid paralysis surveillance performance before and during the 2014-2015 Ebola virus disease outbreak in Guinea and Liberia. *Pan Afr Med J*, *45*, 190. https://doi.org/10.11604/pamj.2023.45.190.21480

UNICEF. (2018). UNICEF_Strategic_Plan_2018-2021-ENG.pdf.

Verani, J. F. S., & Laender, F. (2020). Poliomyelitis eradication in four stages. *Cad Saude Publica*, *36Suppl 2*(Suppl 2), e00145720. https://doi.org/10.1590/0102-311x00145720 (A erradicação da poliomielite em quatro tempos.)

Voorman, A., Lyons, H., Shuaib, F., Adamu, U. S., Korir, C., Erbeto, T., Bandyopadhyay, A. S., & Okiror, S. (2024). Impact of Supplementary Immunization Activities using Novel Oral Polio Vaccine Type 2 during a Large outbreak of Circulating Vaccine-Derived Poliovirus in Nigeria. *J Infect Dis*, *229*(3), 805-812. https://doi.org/10.1093/infdis/jiad222

Wang, X., & Cheng, Z. (2020). Cross-Sectional Studies: Strengths, Weaknesses, and Recommendations. *Chest*, *158*(1s), S65-s71. https://doi.org/10.1016/j.chest.2020.03.012

Wasswa, R., Kananura, R. M., Waiswa, P., Requejo, J. H., Santos, T. M., & Barros, A. J. D. (2025). Subnational trends and inequalities of under-immunisation and zero-dose among children aged 12-23 months in Uganda: a national population-based cross-sectional study. *BMJ Open*, *15*(1), e093619. https://doi.org/10.1136/bmjopen-2024-093619

Watkins, R. E., Martin, P. A. J., Kelly, H., Madin, B., & Watson, C. (2009). An evaluation of the sensitivity of acute flaccid paralysis surveillance for poliovirus infection in Australia. *BMC infectious diseases*, *9*(100968551), 162. https://doi.org/https://dx.doi.org/10.1186/1471-2334-9-162

Wells, J., Young, J. J., Harvey, C., Mutch, H., McPhail, D., Young, N., Wallace, L. A., Ladbury, G., Murray, J. L. K., & Evans, J. M. M. (2022). Real-time surveillance of severe acute respiratory infections in Scottish hospitals: an electronic register-based approach, 2017–2022. *Public Health*, *213*, 5-11. https://library-search.imperial.ac.uk/primo-explore/openurl?vid=ICL_VU1&institution=44IMP&?sid=OVID&isbn=&issn=0033-3506&volume=213&issue=&date=2022&title=Public+Health&atitle=Real-time+surveillance+of+severe+acute+respiratory+infections+in+Scottish+hospihttps://pmc.ncbi.nlm.nih.gov/articles/PMC9595330/

WHO. (2021a). Leave no one behind: guidance for planning and implementing catch-up vaccination

WHO. (2021b). *Polio-Eradication-Strategy-2022-2026-Delivering-on-a-Promise.pdf*.

WHO. (2025a). *Essential Programme on Immunizationhttps://www.who.int/teams/immunization-vaccines-and-biologicals/essential-programme-on-immunization/implementation/global-routine-immunization-strategies-and-practices-(grisp)*.

WHO. (2025b). *Immunisation Data*. https://immunizationdata.who.int/global?topic=&location=

WHO, GAVI, IA2030, & UNICEF. (2023). The Big Catch-Up. An Essential Immunization Recovery Plan FOR 2023 AND BEYOND.pdf.

WHO, & UNICEF. (2021). *WHO and UNICEF estimates of immunization coverage: 2021 revision*.

WHO, & UNICEF. (2022). WHO/UNICEF Estimate of National Immunization Coverage 20221.

WHO, & UNICEF. (2023). *WHO and UNICEF estimates of immunization coverage: 2023 revision*.

WHO., & PAHO. (2016). Planning and Implementing High-Quality Supplementary Immunisation Activities for Injectable Vaccines: Using an Example of Measles and Rubella Vaccines. https://iris.who.int/bitstream/handle/10665/330568/9789241511254-eng.pdf

WHO/UNICEF. (2019). WHOUNICEF_Progress and Challenges with Achieving Universal Immunization Coverage.pdf>.

Wigley, A., Lorin, J., Hogan, D., Utazi, C. E., Hagedorn, B., Dansereau, E., Tatem, A. J., & Tejedor-Garavito, N. (2022). Estimates of the number and distribution of zero-dose and under-immunised children across remote-rural, urban, and conflict-affected settings in low and middle-income countries. *PLOS Glob Public Health*, *2*(10), e0001126. https://doi.org/10.1371/journal.pgph.0001126

Wolter, K. K., Smith, P. J., Khare, M., Welch, B., Copeland, K. R., Pineau, V. J., & Davis, N. (2017). Statistical Methodology of the National Immunization Survey, 2005-2014. *Vital Health Stat 1*(61), 1-107.

Appendices

Annex 1- AFP case based surveillance and NICS OPV coverage data

State	AFP_Scases	AFP_OPV_0dose	AFP_OPV_1_2dose	AFP_OPV_3dose	AFP_unknown_dose	AFP_OPV3_Cov_%	NICS_OPV3_cov_%
Abia	214	6	25	181	2	87.91946	59.2
Adamawa	378	44	41	287	6	76.49254	50.2
Akwa Ibom	311	36	42	225	8	73.86364	73.7
Anambra	281	12	18	238	13	90.81081	64.3
Bauchi	533	291	66	151	25	32.27991	39.6
Bayelsa	146	18	20	105	3	80.95238	52.9
Benue	185	22	26	131	6	67.7686	60.7
Borno	460	293	52	98	17	22.84123	31
Cross Rive	97	3	7	83	4	86.07595	73.8
Delta	129	7	20	93	9	77.89474	62.1
Ebonyi	127	9	12	103	3	82.69231	97.9
Edo	131	5	8	115	3	89.13043	72.1
Ekiti	178	1	11	166	0	93.39623	76.3
Enugu	376	16	40	285	35	79.00763	77.8
FCT, Abuja	119	19	8	92	0	76.62338	75.7
Gombe	308	83	28	196	1	60.55046	40.2
Imo	197	8	29	158	2	85.8209	80.9
Jigawa	958	363	85	486	24	53.89222	51.8
Kaduna	426	147	31	233	15	54.90196	60.6
Kano	549	285	31	202	31	40.9611	45.5
Katsina	346	208	15	91	32	31.06061	55.1
Kebbi	651	444	10	172	11	31.86373	61.5
Kogi	157	13	21	119	4	75.75758	56.9
Kwara	235	81	19	131	4	53.75	54.1
Lagos	257	9	14	233	1	94.65241	77.6
Nasarawa	178	70	13	90	5	54.7619	47.6
Niger	320	71	21	228	0	75.9434	46.6
Ogun	138	4	5	127	2	98.91304	43.2
Ondo	190	2	9	179	0	96.55172	58.1
Osun	114	4	17	93	0	87.34177	65.2
Oyo	267	29	18	216	4	79.12088	49.6
Plateau	269	75	18	167	9	69.14286	58.5
Rivers	375	7	46	314	8	79.5082	67
Sokoto	166	133	7	20	6	13.07692	21
Taraba	236	64	31	138	3	58.33333	51.3
Yobe	237	68	7	81	81	37.1134	63.2
Zamfara	252	179	5	28	40	12.37624	35.1

Annex 2- Suspected AFP case by LGA in Nigeria

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Abia	Aba North	16	21	37
Abia	Aba South	5	12	17
Abia	Arochukwu	5	4	9
Abia	Bende	5	4	9
Abia	Ikwuano	13	6	19
Abia	Isiala-Ngwa North	12	8	20
Abia	Isiala-Ngwa South	8	5	13
Abia	Isuikwuato	0	5	5
Abia	Obi Nwga	4	4	8
Abia	Ohafia	4	0	4
Abia	Osisioma Ngwa	11	5	16
Abia	Ugwunagbo	3	2	5
Abia	Ukwa East	3	3	6
Abia	Ukwa West	5	3	8
Abia	Umuahia North	8	11	19
Abia	Umuahia South	4	7	11
Abia	Umu-Nneochi	2	6	8
Adamawa	Demsa	3	8	11
Adamawa	Fufore	9	19	28
Adamawa	Ganye	6	4	10
Adamawa	Girei	5	6	11
Adamawa	Gombi	1	8	9
Adamawa	Guyuk	4	4	8
Adamawa	Hong	5	10	15
Adamawa	Jada	10	10	20
Adamawa	Lamurde	5	5	10
Adamawa	Madagali	14	14	28
Adamawa	Maiha	3	13	16
Adamawa	Mayo-Belwa	15	19	34
Adamawa	Michika	11	15	26
Adamawa	Mubi North	10	28	38
Adamawa	Mubi South	4	17	21
Adamawa	Numan	4	5	9
Adamawa	Shelleng	6	9	15
Adamawa	Song	5	7	12
Adamawa	Toungo	5	6	11
Adamawa	Yola North	13	11	24

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Adamawa	Yola South	11	11	22
Akwa Ibom	Abak	8	0	8
Akwa Ibom	Eastern Obolo	2	1	3
Akwa Ibom	Eket	2	2	4
Akwa Ibom	Esit Eket	3	1	4
Akwa Ibom	Essien Udim	5	8	13
Akwa Ibom	Etim Ekpo	5	3	8
Akwa Ibom	Etinan	13	18	31
Akwa Ibom	Ibeno	3	2	5
Akwa Ibom	Ibesikpo Asutan	8	9	17
Akwa Ibom	Ibiono Ibom	3	4	7
Akwa Ibom	Ika	3	4	7
Akwa Ibom	Ikono	6	5	11
Akwa Ibom	Ikot Abasi	9	6	15
Akwa Ibom	Ikot Ekpene	4	3	7
Akwa Ibom	Ini	3	2	5
Akwa Ibom	Itu	5	3	8
Akwa Ibom	Mbo	6	5	11
Akwa Ibom	Mkpat Enin	7		7
Akwa Ibom	Nsit Atai	1	2	3
Akwa Ibom	Nsit Ibom	4	4	8
Akwa Ibom	NSIT UBIUM	3	10	13
Akwa Ibom	Obot Akara	1	6	7
Akwa Ibom	Okobo	3	7	10
Akwa Ibom	Onna	4	6	10
Akwa Ibom	Oron	2	2	4
Akwa Ibom	Oruk Anam	3	5	8
Akwa Ibom	Udung Uko	7	10	17
Akwa Ibom	Ukanafun	4	4	8
Akwa Ibom	Uruan	4	6	10
Akwa Ibom	Urue Offong/Oruko	7	2	9
Akwa Ibom	Uyo	10	23	33
Anambra	Aguata	10	5	15
Anambra	Anambra East	1	5	6
Anambra	Anambra West	0	4	4
Anambra	Anaocha	4	3	7
Anambra	Awka North	3	5	8
Anambra	Awka South	10	5	15
Anambra	Ayamelum	0	4	4
Anambra	Dunukofia	3	4	7
Anambra	Ekwusigo	7	8	15

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Anambra	Idemili North	3	8	11
Anambra	Idemili South	19	26	45
Anambra	Ihiala	2	11	13
Anambra	Njikoka	4	4	8
Anambra	Nnewi North	8	11	19
Anambra	Nnewi South	12	4	16
Anambra	Ogbaru	7	11	18
Anambra	Onitsha North	9	16	25
Anambra	Onitsha South	7	15	22
Anambra	Orumba North	1	3	4
Anambra	Orumba South	2	4	6
Anambra	Oyi	7	6	13
Bauchi	Alkaleri	11	14	25
Bauchi	Bauchi	19	14	33
Bauchi	Bogoro	6	3	9
Bauchi	Damban	12	19	31
Bauchi	Darazo	17	29	46
Bauchi	Dass	4	4	8
Bauchi	Gamawa	19	12	31
Bauchi	Ganjuwa	5	15	20
Bauchi	Giade	9	6	15
Bauchi	Itas/Gadau	28	16	44
Bauchi	Jama'are	11	25	36
Bauchi	Katagum	9	17	26
Bauchi	Kirfi	9	10	19
Bauchi	Misau	11	18	29
Bauchi	Ningi	4	10	14
Bauchi	Shira	8	15	23
Bauchi	Tafawa-Balewa	12	18	30
Bauchi	Toro	20	29	49
Bauchi	Warji	2	7	9
Bauchi	Zaki	10	26	36
Bayelsa	Brass	12	7	19
Bayelsa	Ekeremor	8	12	20
Bayelsa	Kolokuma/Opokuma	4	5	9
Bayelsa	Nembe	11	6	17
Bayelsa	Ogbia	15	14	29
Bayelsa	Sagbama	7	9	16
Bayelsa	Southern Ijaw	8	4	12
Bayelsa	Yenegoa	10	14	24
Benue	Ado	3	4	7

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Benue	Agatu	5	13	18
Benue	Apa	3	5	8
Benue	Buruku	1	5	6
Benue	Gboko	2	6	8
Benue	Guma	4	1	5
Benue	Gwer East	1	3	4
Benue	Gwer West	4	7	11
Benue	Katsina-Ala	4	6	10
Benue	Konshisha	1	1	2
Benue	Kwande	3	3	6
Benue	Logo	0	4	4
Benue	Makurdi	4	9	13
Benue	Obi	2	5	7
Benue	Ogbadibo	4	7	11
Benue	Ohimini	0	2	2
Benue	Oju	4	13	17
Benue	Okpokwu	9	12	21
Benue	Oturkpo	1	3	4
Benue	Tarka	0	2	2
Benue	Ukum	1	4	5
Benue	Ushongo	4	2	6
Benue	Vandeikya	1	7	8
Borno	Abadam	4	5	9
Borno	Askira/Uba	12	8	20
Borno	Bama	15	15	30
Borno	Bayo	4	2	6
Borno	Biu	6	8	14
Borno	Chibok	5	2	7
Borno	Damboa	14	8	22
Borno	Dikwa	13	9	22
Borno	Gubio	7	11	18
Borno	Guzamala	5	11	16
Borno	Gwoza	9	5	14
Borno	Hawul	3	7	10
Borno	Jere	18	21	39
Borno	Kaga	3	5	8
Borno	Kala/Balge	13	14	27
Borno	Konduga	8	12	20
Borno	Kukawa	7	13	20
Borno	Kwaya Kusar	3	3	6
Borno	Mafa	3	1	4

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Borno	Magumeri	7	17	24
Borno	Maiduguri	7	14	21
Borno	Marte	13	10	23
Borno	Mobbar	10	6	16
Borno	Monguno	8	7	15
Borno	Ngala	11	14	25
Borno	Nganzai	9	10	19
Borno	Shani	0	5	5
Cross_River	Abi	0	3	3
Cross_River	Akamkpa	1	2	3
Cross_River	Akpabuyo	4	4	8
Cross_River	Bakassi	2	1	3
Cross_River	Bekwarra	1	3	4
Cross_River	Biase	3	4	7
Cross_River	Boki	4	4	8
Cross_River	Calabar Municipal	1	4	5
Cross_River	Calabar South	3	2	5
Cross_River	Etung	1	2	3
Cross_River	Ikom	6	5	11
Cross_River	Obanliku	7	4	11
Cross_River	Obubra	3	3	6
Cross_River	Obudu	0	2	2
Cross_River	Odukpani	1	2	3
Cross_River	Ogoja	0	5	5
Cross_River	Yakurr	2	2	4
Cross_River	Yala	2	4	6
Delta	Aniocha North	3	2	5
Delta	Aniocha South	2	5	7
Delta	Bomadi	1	1	2
Delta	Burutu	2	3	5
Delta	Ethiope East	1	2	3
Delta	Ethiope West	1	2	3
Delta	Ika North East	1	5	6
Delta	Ika South	1	5	6
Delta	Isoko North	2	3	5
Delta	Isoko South	0	2	2
Delta	Ndokwa East	3	4	7
Delta	Ndokwa West	3	3	6
Delta	Okpe	3	3	6
Delta	Oshimili North	3	2	5
Delta	Oshimili South	5	4	9

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Delta	Patani	1	4	5
Delta	Sapele	2	3	5
Delta	Udu	2	2	4
Delta	Ughelli North	1	8	9
Delta	Ughelli South	2	5	7
Delta	Ukwuani	0	4	4
Delta	Uvwie	0	3	3
Delta	Warri North	2	1	3
Delta	Warri South	4	3	7
Delta	Warri South-West	2	3	5
Ebonyi	Abakaliki	5	6	11
Ebonyi	Afikpo North	6	9	15
Ebonyi	Afikpo South	3	2	5
Ebonyi	Ebonyi	4	9	13
Ebonyi	Ezza North	2	2	4
Ebonyi	Ezza South	2	2	4
Ebonyi	Ikwo	5	4	9
Ebonyi	Ishielu	4	4	8
Ebonyi	Ivo	4	2	6
Ebonyi	Izzi	4	7	11
Ebonyi	Ohaozara	7	11	18
Ebonyi	Ohaukwu	4	13	17
Ebonyi	Onicha	3	3	6
Edo	Akoko-Edo	3	4	7
Edo	Egor	0	2	2
Edo	Esan Central	1	1	2
Edo	Esan North-East	3	2	5
Edo	Esan South-East	5	4	9
Edo	Esan West	2	0	2
Edo	Etsako Central	1	2	3
Edo	Etsako East	2	7	9
Edo	Etsako West	2	5	7
Edo	Iguegben	3	3	6
Edo	Ikpoba-Okha	10	4	14
Edo	Oredo	6	2	8
Edo	Orhionmwon	5	6	11
Edo	Ovia North-East	1	2	3
Edo	Ovia South-West	8	16	24
Edo	Owan East	2	3	5
Edo	Owan West	0	3	3
Edo	Uhunmwonde	3	8	11

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Ekiti	Ado-Ekiti	7	7	14
Ekiti	Efon	7	5	12
Ekiti	Ekiti East	2	4	6
Ekiti	Ekiti South-West	4	4	8
Ekiti	Ekiti West	2	7	9
Ekiti	Emure	5	6	11
Ekiti	Gbonyin	10	4	14
Ekiti	Ido-Osi	3	8	11
Ekiti	Ijero	2	7	9
Ekiti	Ikere	2	8	10
Ekiti	Ikole	9	2	11
Ekiti	Ilejemeje	6	4	10
Ekiti	Irepodun/Ifelodun	6	8	14
Ekiti	Ise/Orun	5	7	12
Ekiti	Moba	8	5	13
Ekiti	Oye	8	6	14
Enugu	Aninri	7	13	20
Enugu	Awgu	7	9	16
Enugu	Enugu East	5	3	8
Enugu	Enugu North	4	4	8
Enugu	Enugu South	5	11	16
Enugu	Ezeagu	12	18	30
Enugu	Igbo-Etiti	5	9	14
Enugu	Igbo-Eze-North	21	32	53
Enugu	Igbo-Eze-South	4	12	16
Enugu	Isi-Uzo	5	8	13
Enugu	Nkanu East	3	6	9
Enugu	Nkanu West	9	18	27
Enugu	Nsukka	22	31	53
Enugu	Oji-River	14	7	21
Enugu	Udenu	12	18	30
Enugu	Udi	7	14	21
Enugu	Uzo-Uwani	12	9	21
FCT_Abuja	Abaji	4	8	12
FCT_Abuja	Bwari	7	22	29
FCT_Abuja	Gwagwalada	7	14	21
FCT_Abuja	Kuje	13	8	21
FCT_Abuja	Kwali	5	11	16
FCT_Abuja	Municipal Area Council	7	13	20

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Gombe State	Gombe	129	179	308
Gombe State	Akko	11	21	32
Gombe State	Balanga	8	15	23
Gombe State	Billiri	14	9	23
Gombe State	Dukku	17	24	41
Gombe State	Funakaye	15	24	39
Gombe State	Gombe	11	15	26
Gombe State	Kaltungo	6	9	15
Gombe State	Kwami	19	17	36
Gombe State	Nafada	7	15	22
Gombe State	Shomgom	15	17	32
Gombe State	Yamaltu/Deba	6	13	19
Imo	Aboh-Mbaise	0	5	5
Imo	Ahiazu-Mbaise	4	4	8
Imo	Ehime-Mbano	3	4	7
Imo	Ezinihitte	3	8	11
Imo	Ideato North	2	4	6
Imo	Ideato South	5	1	6
Imo	Ihitte/Uboma	5	3	8
Imo	Ikeduru	3	0	3
Imo	Isiala Mbano	1	2	3
Imo	Isu	1	6	7
Imo	Mbatoli	5	7	12
Imo	Ngor-Okpala	5	9	14
Imo	Njaba	0	4	4
Imo	Nkwerre	4	1	5
Imo	Nwangele	2	1	3
Imo	OBOWO	7	3	10
Imo	Oguta	3	3	6
Imo	Ohaji/Egbema	7	4	11
Imo	Okigwe	2	3	5
Imo	Onuimo	1	7	8

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Imo	Orlu	5	6	11
Imo	Orsu	1	2	3
Imo	Oru East	1	4	5
Imo	Oru West	1	1	2
Imo	Owerri Municipal	8	4	12
Imo	Owerri North	3	5	8
Imo	Owerri West	8	6	14
Jigawa	Auyo	16	19	35
Jigawa	Babura	16	13	29
Jigawa	Birnin Kudu	44	38	82
Jigawa	Birniwa	21	13	34
Jigawa	Buji	14	12	26
Jigawa	Dutse	82	84	166
Jigawa	Gagarawa	16	27	43
Jigawa	Garki	9	6	15
Jigawa	Gumel	10	9	19
Jigawa	Guri	4	11	15
Jigawa	Gwaram	15	24	39
Jigawa	Gwiwa	15	7	22
Jigawa	Hadejia	8	12	20
Jigawa	Jahun	9	11	20
Jigawa	Kafin Hausa	9	15	24
Jigawa	Kaugama	17	21	38
Jigawa	Kazaure	4	13	17
Jigawa	Kiri Kasama	8	4	12
Jigawa	Kiyawa	15	20	35
Jigawa	Maigatari	7	12	19
Jigawa	Malam Maduri	25	21	46
Jigawa	Miga	11	14	25
Jigawa	Ringim	17	15	32
Jigawa	Roni	6	17	23
Jigawa	Sule Tankarkar	8	8	16
Jigawa	Taura	36	50	86
Jigawa	Yankwashi	9	11	20
Kaduna	Birnin Gwari	5	6	11
Kaduna	Chikun	11	14	25
Kaduna	Giwa	15	11	26
Kaduna	Igabi	13	20	33
Kaduna	Ikara	13	12	25
Kaduna	Jaba	1	5	6
Kaduna	Jema'A	4	9	13

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Kaduna	Kachia	5	6	11
Kaduna	Kaduna North	8	13	21
Kaduna	Kaduna South	8	19	27
Kaduna	Kagarko	2	4	6
Kaduna	Kajuru	4	11	15
Kaduna	Kaura	3	6	9
Kaduna	Kauru	6	8	14
Kaduna	Kubau	5	9	14
Kaduna	Kudan	13	8	21
Kaduna	Lere	12	13	25
Kaduna	Makarfi	5	13	18
Kaduna	Sabon Gari	14	15	29
Kaduna	Sanga	4	8	12
Kaduna	Soba	7	10	17
Kaduna	Zangon Kataf	4	5	9
Kaduna	Zaria	21	18	39
Kano	Ajingi	3	6	9
Kano	Albasu	8	8	16
Kano	Bagwai	6	8	14
Kano	Bebeji	5	4	9
Kano	Bichi	11	5	16
Kano	Bunkure	0	6	6
Kano	Dala	4	12	16
Kano	Dambatta	5	10	15
Kano	Dawakin Kudu	4	12	16
Kano	Dawakin Tofa	6	4	10
Kano	Doguwa	3	5	8
Kano	Fagge	4	8	12
Kano	Gabasawa	2	6	8
Kano	Garko	8	2	10
Kano	Garum Mallam	4	4	8
Kano	Gaya	10	29	39
Kano	Gezawa	5	11	16
Kano	Gwale	3	8	11
Kano	Gwarzo	4	14	18
Kano	Kabo	3	4	7
Kano	Kano Municipal	4	4	8
Kano	Karaye	5	5	10
Kano	Kibiya	2	2	4
Kano	Kiru	6	2	8
Kano	Kumbotso	5	4	9

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Kano	Kunchi	2	3	5
Kano	Kura	3	3	6
Kano	Madobi	2	4	6
Kano	Makoda	4	4	8
Kano	Minjibir	8	5	13
Kano	Nassarawa	6	12	18
Kano	Rano	0	4	4
Kano	Rimin Gado	6	5	11
Kano	Rogo	13	10	23
Kano	Shanono	6	11	17
Kano	Sumaila	3	5	8
Kano	Takai	3	6	9
Kano	Tarauni	15	14	29
Kano	Tofa	3	4	7
Kano	Tsanyawa	5	2	7
Kano	Tudun Wada	1	7	8
Kano	Ungogo	22	28	50
Kano	Warawa	4	5	9
Kano	Wudil	4	4	8
Katsina	Bakori	8	5	13
Katsina	Batagarawa	2	7	9
Katsina	Batsari	7	3	10
Katsina	Baure	3	3	6
Katsina	Bindawa	2	4	6
Katsina	Charanchi	7	8	15
Katsina	Dan Musa	4	6	10
Katsina	Dandume	2	10	12
Katsina	Danja	4	3	7
Katsina	Daura	4	8	12
Katsina	Dutsi	5	3	8
Katsina	Dutsin Ma	6	4	10
Katsina	Faskari	5	4	9
Katsina	Funtua	7	6	13
Katsina	Ingawa	5	2	7
Katsina	Jibia	7	8	15
Katsina	Kafur	2	4	6
Katsina	Kaita	5	6	11
Katsina	Kankara	7	8	15
Katsina	Kankia	3	8	11
Katsina	Katsina	4	7	11
Katsina	Kurfi	5	4	9

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Katsina	Kusada	2	4	6
Katsina	Mai'Adua	4	7	11
Katsina	Malumfashi	9	5	14
Katsina	Mani	1	5	6
Katsina	Mashi	5	7	12
Katsina	Matazu	6	6	12
Katsina	Musawa	6	2	8
Katsina	Rimi	3	2	5
Katsina	Sabuwa	9	3	12
Katsina	Safana	2	11	13
Katsina	Sandamu	6	4	10
Katsina	Zango	5	7	12
Kebbi	Aleiro	13	8	21
Kebbi	Arewa Dandi	19	31	50
Kebbi	Argungu	14	24	38
Kebbi	Augie	11	18	29
Kebbi	Bagudo	19	26	45
Kebbi	Birnin Kebbi	15	15	30
Kebbi	Bunza	8	12	20
Kebbi	Dandi	15	21	36
Kebbi	Fakai	10	11	21
Kebbi	Gwandu	4	17	21
Kebbi	Jega	16	15	31
Kebbi	Kalgo	11	27	38
Kebbi	Koko/Besse	17	10	27
Kebbi	Maiyama	8	11	19
Kebbi	Ngaski	23	26	49
Kebbi	Sakaba	14	20	34
Kebbi	Shanga	16	22	38
Kebbi	Suru	6	10	16
Kebbi	Wasagu/Danko	15	21	36
Kebbi	Yauri	7	16	23
Kebbi	Zuru	12	17	29
Kogi	Adavi	5	8	13
Kogi	Ajaokuta	1	6	7
Kogi	Ankpa	5	7	12
Kogi	Bassa	2	3	5
Kogi	Dekina	8	11	19
Kogi	Ibaji	7	6	13
Kogi	Idah	0	3	3
Kogi	Igalamela-Odolu	5	2	7

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Kogi	Ijumu	2	1	3
Kogi	Kabba/Bunu	3	1	4
Kogi	Kogi	1	3	4
Kogi	Lokoja	1	5	6
Kogi	Mopa-Muro	5	1	6
Kogi	Ofu	2	2	4
Kogi	Ogori/Magongo	1	1	2
Kogi	Okehi	1	2	3
Kogi	Okene	1	5	6
Kogi	Olamaboro	8	10	18
Kogi	Omala	1	7	8
Kogi	Yagba East	4	4	8
Kogi	Yagba West	2	4	6
Kwara	Asa	4	9	13
Kwara	Baruten	14	28	42
Kwara	Edu	12	12	24
Kwara	Ekiti	1	2	3
Kwara	Ifelodun	1	6	7
Kwara	Ilorin East	3	7	10
Kwara	Ilorin South	2	9	11
Kwara	Ilorin West	5	9	14
Kwara	Irepodun	0	8	8
Kwara	Isin	2	4	6
Kwara	Kaiama	20	30	50
Kwara	Moro	5	17	22
Kwara	Offa	2		2
Kwara	Oke Ero	1	4	5
Kwara	Oyun	2	9	11
Kwara	Pategi	2	5	7
Lagos	Agege	4	7	11
Lagos	Ajeromi/Ifelodun	8	10	18
Lagos	Alimosho	13	19	32
Lagos	Amuwo Odofin	3	7	10
Lagos	Apapa	3	2	5
Lagos	Badagry	3	6	9
Lagos	Epe	6	6	12
Lagos	Eti Osa	4	6	10
Lagos	Ibeju Lekki	1	4	5
Lagos	Ifako/Ijaye	2	10	12
Lagos	Ikeja	3	2	5
Lagos	Ikorodu	5	11	16

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Lagos	Kosofe	8	7	15
Lagos	Lagos Island	1	8	9
Lagos	Lagos Mainland	2	8	10
Lagos	Mushin	8	6	14
Lagos	Ojo	7	10	17
Lagos	Oshodi/Isolo	3	17	20
Lagos	Shomolu	3	9	12
Lagos	Surulere	5	10	15
Nasarawa	Akwanga	2	3	5
Nasarawa	Awe	3	8	11
Nasarawa	Doma	6	5	11
Nasarawa	Karu	10	19	29
Nasarawa	Keana	5	5	10
Nasarawa	Keffi	4	14	18
Nasarawa	Kokona	0	6	6
Nasarawa	Lafia	4	6	10
Nasarawa	Nasarawa	19	19	38
Nasarawa	Nasarawa Egon		2	2
Nasarawa	Obi	1	4	5
Nasarawa	Toto	14	15	29
Nasarawa	Wamba	0	4	4
Niger	Agaie	2	14	16
Niger	Agwara	4	7	11
Niger	Bida	0	5	5
Niger	Borgu	3	5	8
Niger	Bosso	7	12	19
Niger	Chanchaga	8	14	22
Niger	Edati	4	6	10
Niger	Gbako	10	4	14
Niger	Gurara	3	3	6
Niger	Katcha	3	3	6
Niger	Kontagora	2	4	6
Niger	Lapai	4	5	9
Niger	Lavun	2	9	11
Niger	Magama	6	5	11
Niger	Mariga	3	5	8
Niger	Mashegu	3	8	11
Niger	Mokwa	10	8	18
Niger	Munya	7	12	19
Niger	Paikoro	6	8	14
Niger	Rafi	4	5	9

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Niger	Rijau	3	3	6
Niger	Shiroro	16	22	38
Niger	Suleja	15	15	30
Niger	Tafa	0	6	6
Niger	Wushishi	5	2	7
Ogun	Abeokuta North	6		6
Ogun	Abeokuta South	3	7	10
Ogun	Ado Odo/Ota	2	8	10
Ogun	Ewekoro	1	1	2
Ogun	Ifo	9	3	12
Ogun	Ijebu East	5	1	6
Ogun	Ijebu North	3	6	9
Ogun	Ijebu North East	4	3	7
Ogun	Ijebu Ode	6	7	13
Ogun	Ikenne	2	2	4
Ogun	Imeko Afon	4	4	8
Ogun	Ipokia	2	2	4
Ogun	Obafemi Owode	2	6	8
Ogun	Odeda	1	2	3
Ogun	Odogbolu	1	2	3
Ogun	Ogun Waterside	1	3	4
Ogun	Remo North	2	3	5
Ogun	Shagamu	3	7	10
Ogun	Yewa North	3	6	9
Ogun	Yewa South	3	2	5
Ondo	Akoko North East	4	9	13
Ondo	Akoko North West	8	8	16
Ondo	Akoko South East	4	6	10
Ondo	Akoko South West	5	8	13
Ondo	Akure North	7	4	11
Ondo	Akure South	4	9	13
Ondo	Ese Odo	4	2	6
Ondo	Idanre	3	2	5
Ondo	Ifedore	3	4	7
Ondo	Ilaje	1	5	6
Ondo	Ile Oluji/Okeigbo	1	5	6
Ondo	Irele	4	16	20
Ondo	Odigbo	2	2	4
Ondo	Okitipupa	11	11	22
Ondo	Ondo East	5	1	6
Ondo	Ondo West	5	4	9

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Ondo	Ose	8	2	10
Ondo	Owo	1	12	13
Osun	Atakunmosa East	2	2	4
Osun	Atakunmosa West	2	2	4
Osun	Ayedade	4	1	5
Osun	Ayedire	1	2	3
Osun	Boluwaduro	0	3	3
Osun	Boripe	1	1	2
Osun	Ede North	2	7	9
Osun	Ede South	0	5	5
Osun	Egbedore	2	5	7
Osun	Ejigbo	1	7	8
Osun	Ife Central	2	2	4
Osun	Ife East	1	1	2
Osun	Ife North	0	2	2
Osun	Ife South	5	2	7
Osun	Ifedayo	0	2	2
Osun	Ifelodun	1	0	1
Osun	Ila	1	0	1
Osun	Ilesha East	0	3	3
Osun	Ilesha West	3	2	5
Osun	Irepodun	2	4	6
Osun	Irewole	0	3	3
Osun	Isokan	1	1	2
Osun	Iwo	2	1	3
Osun	Obokun	1	1	2
Osun	Odo Otin	1	0	1
Osun	Ola Oluwa	3	0	3
Osun	Olorunda	0	4	4
Osun	Oriade	1	2	3
Osun	Orolu	2	1	3
Osun	Osogbo	4	3	7
Oyo	Afijio	2	4	6
Oyo	Akinyele	3	3	6
Oyo	Atiba	0	8	8
Oyo	Atisbo	5	3	8
Oyo	Egbeda	5	3	8
Oyo	Ibadan North	6	2	8
Oyo	Ibadan North East	3	5	8
Oyo	Ibadan North West	3	5	8
Oyo	Ibadan South East	4	9	13

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Oyo	Ibadan South West	2	6	8
Oyo	Ibarapa Central	8	5	13
Oyo	Ibarapa East	3	3	6
Oyo	Ibarapa North	4	8	12
Oyo	Ido	1	5	6
Oyo	Irepo	2	5	7
Oyo	Iseyin	3	4	7
Oyo	Itesiwaju	4	9	13
Oyo	Iwajowa	3	2	5
Oyo	Kajola	6	3	9
Oyo	Lagelu	3	2	5
Oyo	Ogbomosho North	3	6	9
Oyo	Ogbomosho South	3	3	6
Oyo	Ogo Oluwa	1	3	4
Oyo	Olorunsogo	2	4	6
Oyo	Oluyole	4	5	9
Oyo	Ona ara	4	3	7
Oyo	Orelope	0	6	6
Oyo	Ori Ire	4	4	8
Oyo	Oyo East	3	3	6
Oyo	Oyo West	2	13	15
Oyo	Saki East	5	3	8
Oyo	Saki West	5	8	13
Oyo	Surulere	3	3	6
Plateau	Barkin Ladi	7	11	18
Plateau	Bassa	2	10	12
Plateau	Bokkos	4	4	8
Plateau	Jos East	6	4	10
Plateau	Jos North	11	15	26
Plateau	Jos South	6	14	20
Plateau	Kanam	14	19	33
Plateau	Kanke	4	12	16
Plateau	Langtang North	9	2	11
Plateau	Langtang South	5	2	7
Plateau	Mangu	3	11	14
Plateau	Mikang	5	6	11
Plateau	Pankshin	1	5	6
Plateau	Qua'an Pan	5	19	24
Plateau	Riyom	2	6	8
Plateau	Shendam	5	6	11
Plateau	Wase	11	23	34

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Rivers	ABUA/ODUAL	9	16	25
Rivers	Ahoada East	2	3	5
Rivers	Ahoada West	3	7	10
Rivers	Akuku Toru	6	6	12
Rivers	Andoni	10	7	17
Rivers	Asari-Toru	9	5	14
Rivers	Bonny	12	11	23
Rivers	Degema	5	10	15
Rivers	Eleme	4	6	10
Rivers	Emuoha	7	5	12
Rivers	Etche	18	7	25
Rivers	GOKANA	10	2	12
Rivers	Ikwerre	5	12	17
Rivers	Khana	9	11	20
Rivers	Obio/Akpor	1	13	14
Rivers	Ogba/Egbema/Ndoni	15	16	31
Rivers	Ogu Bolo	4	4	8
Rivers	Okrika	6	6	12
Rivers	Omumma	9	17	26
Rivers	Opobo/Nkoro	8	9	17
Rivers	Oyigbo	4	5	9
Rivers	Port-Harcourt	7	8	15
Rivers	Tai	9	17	26
Sokoto	Binji	3	2	5
Sokoto	Bodinga	4	4	8
Sokoto	Dange-Shuni	2	3	5
Sokoto	Gada	3	8	11
Sokoto	Goronyo	4	5	9
Sokoto	Gudu	2	4	6
Sokoto	Gwadabawa	4	8	12
Sokoto	Illela	4	5	9
Sokoto	Isa	1	2	3
Sokoto	Kebbe	5	4	9
Sokoto	Kware	2	3	5
Sokoto	Rabah	5	5	10
Sokoto	Sabon Birni		8	8
Sokoto	Shagari	1	4	5
Sokoto	Silame	1	4	5
Sokoto	Sokoto North	2	3	5
Sokoto	Sokoto South	9	7	16
Sokoto	Tambuwal	4	3	7

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Sokoto	Tangaza	2	2	4
Sokoto	Tureta	0	6	6
Sokoto	Wamakko	7	3	10
Sokoto	Wurno	4	2	6
Sokoto	Yabo	1	1	2
Taraba	Ardo-Kola	4	9	13
Taraba	Bali	6	6	12
Taraba	Donga	9	9	18
Taraba	Gashaka	4	9	13
Taraba	Gassol	13	16	29
Taraba	Ibi	7	12	19
Taraba	Jalingo	5	7	12
Taraba	Karim Lamido	2	7	9
Taraba	Kurmi	3	6	9
Taraba	Lau	7	5	12
Taraba	Sardauna	12	13	25
Taraba	Takum	5	7	12
Taraba	Ussa	5	5	10
Taraba	Wukari	11	11	22
Taraba	Yorro	3	6	9
Taraba	Zing	4	8	12
Yobe	Bade	4	9	13
Yobe	Bursari	3	4	7
Yobe	Damaturu	4	8	12
Yobe	Fika	10	10	20
Yobe	Fune	7	9	16
Yobe	Geidam	4	8	12
Yobe	Gujba	6	12	18
Yobe	Gulani	5	12	17
Yobe	Jakusko	9	9	18
Yobe	Karasuwa	9	4	13
Yobe	Machina	3	10	13
Yobe	Nangere	6	5	11
Yobe	Nguru	8	4	12
Yobe	Potiskum	4	7	11
Yobe	Tarmuwa	10	7	17
Yobe	Yunusari	5	11	16
Yobe	Yusufari	5	6	11
Zamfara	Anka	12	14	26
Zamfara	Bakura	9	13	22

State	LGA	AFP_Scases_Females	AFP_Scases_Males	AFP_Scases_total
Zamfara	Birnin Magaji/Kiyaw	8	5	13
Zamfara	Bukkuyum	5	8	13
Zamfara	Bungudu	6	8	14
Zamfara	Gummi	15	15	30
Zamfara	Gusau	10	7	17
Zamfara	Kaura Namoda	8	11	19
Zamfara	Maradun	13	6	19
Zamfara	Maru	5	6	11
Zamfara	Shinkafi	9	5	14
Zamfara	Talata Mafara	9	18	27
Zamfara	Tsafe	6	12	18
Zamfara	Zurmi	6	3	9

Annex 3- Zero-dose count by LGA in Nigeria from 2022 AFP data

LGA_12_23_month	No_0dose_12_23	LGA_24_35_month	No_0dose_24_35
Abaji	1	Abaji	1
Adavi	1	Abi	1
Ado	1	Akko	1
Afikpo North	1	Albasu	1
Ajingi	1	Ankpa	1
Akko	1	Apapa	1
Albasu	1	Asa	1
Alimosho	1	Atisbo	1
Auyo	1	Balanga	1
Awe	1	Bali	1
Badagry	1	Bama	1
Balanga	1	Barkin Ladi	1
Bali	1	Bindawa	1
Bebeji	1	Binji	1
Bichi	1	Birnin Gwari	1
Binji	1	Biu	1
Birnin Magaji/Kiyaw	1	Bodinga	1
Buruku	1	Bogoro	1
Bwari	1	Borgu	1
Dandume	1	Bukkuyum	1
Dass	1	Bunkure	1
Dekina	1	Charanchi	1
Dikwa	1	Dutsi	1
Doma	1	Etche	1
Dutsi	1	Gabasawa	1
Eastern Obolo	1	Garko	1
Edu	1	Gashaka	1
Etche	1	Gbako	1
Ezinihitte	1	Gumel	1
Fika	1	Gurara	1
Fufore	1	Guyuk	1
Funakaye	1	Gwer West	1
Gabasawa	1	Gwiwa	1
Ganjuwa	1	Gwoza	1
Geidam	1	Hadejia	1
Gezawa	1	Hawul	1
Gubio	1	Ibarapa Central	1
Gudu	1	Ikot Abasi	1
Gulani	1	Ikwo	1
Guri	1	Ilesha West	1

LGA_12_23_month	No_0dose_12_23	LGA_24_35_month	No_0dose_24_35
Gwarzo	1	Illela	1
Gwer West	1	Ilorin East	1
Gwoza	1	Iseyin	1
Hadejia	1	Isin	1
Hawul	1	Itu	1
Ibarapa Central	1	Jema'A	1
Ibesikpo Asutan	1	Jos North	1
Ideato North	1	Jos South	1
Ido	1	Kabo	1
Ikara	1	Kaduna South	1
Ilorin East	1	Kafur	1
Iseyin	1	Kaita	1
Itesiwaju	1	Kajuru	1
Iwajowa	1	Kaltungo	1
Jada	1	Kankia	1
Jahun	1	Kano Municipal	1
Jos East	1	Karaye	1
Jos South	1	Keana	1
Kabo	1	Keffi	1
Kachia	1	Kiri Kasama	1
Kaduna North	1	Kogi	1
Kafin Hausa	1	Kokona	1
Kaga	1	Kukawa	1
Kajuru	1	Kusada	1
Kala/Balge	1	Kwali	1
Kalgo	1	Lafia	1
Kanam	1	Lamurde	1
Kankia	1	Langtang North	1
Karu	1	Lapai	1
Katagum	1	Lau	1
Khana	1	Madobi	1
Kukawa	1	Magama	1
Kurfi	1	Mai'Adua	1
Langtang South	1	Maiduguri	1
Lau	1	Mani	1
Magama	1	Maradun	1
Makoda	1	Maru	1
Malumfashi	1	Matazu	1
Mariga	1	Misau	1
Mashi	1	Mobbar	1
Michika	1	Monguno	1

LGA_12_23_month	No_0dose_12_23	LGA_24_35_month	No_0dose_24_35
Minjibir	1	Mubi North	1
Mkpat Enin	1	Nassarawa	1
Monguno	1	Nnewi South	1
Mopa-Muro	1	Ogbadibo	1
Mubi North	1	Ondo East	1
Mubi South	1	Onitsha South	1
Ndokwa East	1	Orlu	1
Nganzai	1	Oron	1
Nguru	1	Rano	1
Ningi	1	Rimin Gado	1
Nsit Ibom	1	Roni	1
Odukpani	1	Sabon Birni	1
Ogbaru	1	Sabon Gari	1
Ogbomosho North	1	Saki East	1
Okobo	1	Shagari	1
Okpe	1	Sumaila	1
Okpokwu	1	Tafawa-Balewa	1
Onuimo	1	Takai	1
Orelope	1	Tambuwal	1
Oron	1	Tangaza	1
Oyun	1	Tarmuwa	1
Pategi	1	Tofa	1
Rabah	1	Tsanyawa	1
Rano	1	Tureta	1
Rijau	1	Udung Uko	1
Rimin Gado	1	Ukwa East	1
Rogo	1	Warawa	1
Sabon Birni	1	Warri South	1
Sabon Gari	1	Wukari	1
Safana	1	Wurno	1
Sagbama	1	Yorro	1
Saki East	1	Zango	1
Silame	1	Abadam	2
Soba	1	Ajingi	2
Sokoto South	1	Anka	2
Suleja	1	Ardo-Kola	2
Suru	1	Bakura	2
Takai	1	Baruten	2
Tangaza	1	Birniwa	2
Tarauni	1	Damboa	2
Toto	1	Danja	2

LGA_12_23_month	No_0dose_12_23	LGA_24_35_month	No_0dose_24_35
Tureta	1	Doguwa	2
Urue Offong/Oruko	1	Donga	2
Uyo	1	Dutsin Ma	2
Wamakko	1	Edu	2
Warawa	1	Fagge	2
Wudil	1	Fune	2
Wurno	1	Gada	2
Yabo	1	Goronyo	2
Yola South	1	Gulani	2
Yorro	1	Igabi	2
Zaki	1	Igbo-Eze-North	2
Zurmi	1	Ikara	2
Aleiro	2	Jahun	2
Alkaleri	2	Jakusko	2
Anka	2	Kafin Hausa	2
Atisbo	2	Kankara	2
Bauchi	2	Katsina	2
Bayo	2	Kaura Namoda	2
Biu	2	Kebbe	2
Dan Musa	2	Kirfi	2
Dandi	2	Kubau	2
Dange-Shuni	2	Kumbotso	2
Dawakin Kudu	2	Kwami	2
Doguwa	2	Kware	2
Dutsin Ma	2	Kwaya Kusar	2
Fune	2	Maigatari	2
Gashaka	2	Mashegu	2
Giade	2	Miga	2
Gwale	2	Musawa	2
Ifelodun	2	Nganzai	2
Igbo-Eze-North	2	Ningi	2
Illela	2	NSIT UBIUM	2
Ingawa	2	Okpokwu	2
Jalingo	2	Qua'an Pan	2
Jos North	2	Safana	2
Kaiama	2	Sagbama	2
Kajola	2	Sandamu	2
Kirfi	2	Shira	2
Kontagora	2	Soba	2
Langtang North	2	Suru	2
Machina	2	Tudun Wada	2

LGA_12_23_month	No_0dose_12_23	LGA_24_35_month	No_0dose_24_35
Magumeri	2	Wamakko	2
Maradun	2	Wase	2
Miga	2	Wudil	2
Moro	2	Yankwashi	2
Nassarawa	2	Yauri	2
NSIT UBIUM	2	Yenegoa	2
Ovia South-West	2	Zurmi	2
Paikoro	2	Zuru	2
Rafi	2	Augie	3
Sandamu	2	Babura	3
Tafawa-Balewa	2	Bauchi	3
Taura	2	Bebeji	3
Toungo	2	Bichi	3
Yola North	2	Birnin Magaji/Kiyaw	3
Zuru	2	Bungudu	3
Bama	3	Dandume	3
Birnin Kudu	3	Faskari	3
Bukkuyum	3	Fika	3
Chanchaga	3	Funakaye	3
Donga	3	Gujba	3
Ika	3	Guma	3
Jere	3	Jibia	3
Jibia	3	Kaga	3
Kankara	3	Kanam	3
Katsina	3	Kaugama	3
Kaugama	3	Kiru	3
Kauru	3	Kiyawa	3
Kubau	3	Konduga	3
Kudan	3	Mafa	3
Kwami	3	Maiyama	3
Lere	3	Malumfashi	3
Maiyama	3	Nafada	3
Mashegu	3	Rabah	3
Nafada	3	Sakaba	3
Toro	3	Silame	3
Udenu	3	Sokoto South	3
Udung Uko	3	Toto	3
Wase	3	Yunusari	3
Yankwashi	3	Zaria	3
Argungu	4	Auyo	4
Augie	4	Bunza	4

LGA_12_23_month	No_0dose_12_23	LGA_24_35_month	No_0dose_24_35
Babura	4	Daura	4
Bungudu	4	Fufore	4
Bunza	4	Funtua	4
Charanchi	4	Guri	4
Dambatta	4	Guzamala	4
Damboa	4	Gwaram	4
Dutse	4	Koko/Besse	4
Fakai	4	Lere	4
Gassol	4	Minjibir	4
Gaya	4	Sabuwa	4
Gusau	4	Shinkafi	4
Gwaram	4	Tarauni	4
Jega	4	Yamaltu/Deba	4
Kiyawa	4	Aleiro	5
Koko/Besse	4	Bakori	5
Konduga	4	Batsari	5
Maru	4	Dan Musa	5
Ringim	4	Dukku	5
Shinkafi	4	Gagarawa	5
Wasagu/Danko	4	Gezawa	5
Bagudo	5	Gubio	5
Bakura	5	Gummi	5
Damban	5	Gwadabawa	5
Dukku	5	Gwandu	5
Gada	5	Moro	5
Giwa	5	Ringim	5
Goronyo	5	Talata Mafara	5
Gujba	5	Toro	5
Gummi	5	Tsafe	5
Gwadabawa	5	Bagudo	6
Birnin Kebbi	6	Damban	6
Gwandu	6	Dikwa	6
Shanga	6	Fakai	6
Talata Mafara	6	Gaya	6
Tsafe	6	Gusau	6
Ungogo	6	Jere	6
Darazo	7	Kaiama	6
Kaura Namoda	7	Machina	6
Misau	7	Ngaski	6
Ngaski	7	Taura	6
Itas/Gadau	8	Zaki	6

LGA_12_23_month	No_0dose_12_23	LGA_24_35_month	No_0dose_24_35
Jama'are	8	Alkaleri	7
Nasarawa	8	Birnin Kebbi	7
Arewa Dandi	9	Dandi	7
Malam Maduri	10	Gassol	7
Zaria	11	Giade	7
NA	NA	Giwa	7
NA	NA	Kalgo	7
NA	NA	Katagum	7
NA	NA	Kudan	7
NA	NA	Magumeri	7
NA	NA	Wasagu/Danko	7
NA	NA	Darazo	8
NA	NA	Rogo	8
NA	NA	Shanga	8
NA	NA	Ungogo	8
NA	NA	Argungu	9
NA	NA	Birnin Kudu	9
NA	NA	Dutse	9
NA	NA	Jama'are	9
NA	NA	Nasarawa	9
NA	NA	Arewa Dandi	10
NA	NA	Ganjuwa	10
NA	NA	Itas/Gadau	10
NA	NA	Jega	10
NA	NA	Malam Maduri	13

Annex 4- Routine Immunisation Coverage from 2022-2024 from DHIS2

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Abia	Aba North	6,118	6,267	61%	57%	108%	105%	89%	83%
Abia	Aba South	24,123	24,714	64%	65%	68%	73%	66%	63%
Abia	Arochukwu	9,687	9,924	59%	54%	64%	58%	75%	70%
Abia	Bende	10,934	11,202	82%	66%	80%	78%	88%	85%
Abia	Ikwuano	7,854	8,046	53%	54%	73%	65%	80%	77%
Abia	Isiala-Ngwa North	8,750	8,964	84%	77%	80%	74%	74%	68%
Abia	Isiala-Ngwa South	7,670	7,858	89%	84%	87%	85%	95%	88%
Abia	Isuikwuato	6,513	6,673	49%	50%	71%	70%	98%	97%
Abia	Obi Nwga	10,326	10,579	51%	41%	56%	53%	72%	64%
Abia	Ohafia	13,952	14,294	53%	54%	68%	65%	78%	72%
Abia	Osisioma Ngwa	12,500	12,806	63%	57%	74%	69%	74%	70%
Abia	Ugwunagbo	4,702	4,817	72%	68%	64%	62%	72%	67%
Abia	Ukwa East	3,350	3,432	123%	113%	118%	108%	107%	100%
Abia	Ukwa West	5,040	5,164	81%	71%	79%	73%	78%	71%
Abia	Umuahia North	12,559	12,866	107%	103%	94%	90%	86%	82%
Abia	Umuahia South	7,887	8,080	57%	53%	72%	66%	82%	75%
Abia	Umu-Nneochi	9,330	9,558	68%	63%	69%	63%	72%	69%
Adamawa	Demsa	10,864	11,137	122%	116%	120%	115%	122%	117%
Adamawa	Fufore	12,494	12,808	120%	115%	123%	117%	120%	116%
Adamawa	Ganye	9,890	10,138	125%	118%	126%	121%	129%	121%
Adamawa	Girei	7,835	8,032	111%	105%	130%	121%	130%	123%
Adamawa	Gombi	8,826	9,047	116%	110%	119%	111%	123%	110%
Adamawa	Guyuk	10,716	10,985	101%	99%	106%	103%	105%	102%
Adamawa	Hong	10,194	10,450	133%	128%	131%	125%	125%	116%
Adamawa	Jada	10,155	10,409	119%	109%	124%	115%	126%	119%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Adamawa	Lamurde	6,799	6,970	120%	113%	121%	114%	121%	115%
Adamawa	Madagali	8,127	8,331	86%	82%	103%	95%	134%	128%
Adamawa	Maiha	6,703	6,872	123%	116%	125%	118%	124%	114%
Adamawa	Mayo-Belwa	9,230	9,461	116%	109%	131%	127%	127%	121%
Adamawa	Michika	9,361	9,596	119%	114%	125%	119%	131%	125%
Adamawa	Mubi North	9,106	9,334	124%	119%	132%	125%	153%	146%
Adamawa	Mubi South	7,772	7,967	121%	115%	119%	117%	112%	107%
Adamawa	Numan	5,468	5,605	86%	77%	106%	97%	105%	94%
Adamawa	Shelleng	8,985	9,210	108%	104%	113%	109%	114%	111%
Adamawa	Song	11,615	11,906	107%	99%	121%	117%	129%	119%
Adamawa	Toungo	3,137	3,215	152%	139%	185%	165%	173%	159%
Adamawa	Yola North	11,949	12,249	138%	129%	134%	128%	151%	151%
Adamawa	Yola South	11,730	12,024	113%	106%	129%	123%	140%	134%
Akwa Ibom	Abak	6,802	6,892	64%	59%	73%	67%	66%	59%
Akwa Ibom	Eastern Obolo	2,961	3,000	65%	61%	59%	49%	94%	78%
Akwa Ibom	Eket	8,439	8,550	50%	42%	77%	68%	87%	81%
Akwa Ibom	Esit Eket	3,115	3,156	78%	72%	90%	81%	111%	106%
Akwa Ibom	Essien Udim	9,422	9,547	66%	59%	79%	72%	79%	70%
Akwa Ibom	Etim Ekpo	5,155	5,223	43%	39%	66%	61%	64%	60%
Akwa Ibom	Etinan	8,279	8,388	67%	60%	77%	84%	72%	62%
Akwa Ibom	Ibeno	3,686	3,735	57%	54%	84%	76%	126%	115%
Akwa Ibom	Ibesikpo Asutan	6,705	6,793	43%	37%	56%	46%	56%	50%
Akwa Ibom	Ibiono Ibom	9,274	9,397	29%	26%	52%	46%	61%	54%
Akwa Ibom	Ika	3,567	3,614	53%	51%	72%	65%	92%	84%
Akwa Ibom	Ikono	6,451	6,536	69%	64%	67%	61%	87%	81%
Akwa Ibom	Ikot Abasi	6,457	6,542	60%	50%	73%	56%	89%	68%
Akwa Ibom	Ikot Ekpene	6,997	7,089	58%	52%	91%	79%	94%	86%
Akwa Ibom	Ini	4,851	4,915	74%	66%	50%	42%	69%	60%
Akwa Ibom	Itu	6,213	6,294	62%	55%	78%	73%	95%	85%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Akwa Ibom	Mbo	5,087	5,154	61%	56%	87%	69%	97%	91%
Akwa Ibom	Mkpat Enin	8,707	8,822	85%	80%	121%	112%	95%	89%
Akwa Ibom	Nsit Atai	3,648	3,696	77%	73%	74%	67%	100%	92%
Akwa Ibom	Nsit Ibom	5,312	5,382	77%	74%	96%	93%	109%	102%
Akwa Ibom	Nsit Ubium	6,271	6,354	24%	18%	49%	40%	56%	49%
Akwa Ibom	Obot Akara	7,252	7,347	58%	55%	81%	75%	86%	79%
Akwa Ibom	Okobo	5,089	5,156	46%	43%	63%	54%	76%	67%
Akwa Ibom	Onna	6,033	6,113	43%	41%	82%	75%	84%	74%
Akwa Ibom	Oron	4,277	4,334	53%	45%	78%	68%	68%	58%
Akwa Ibom	Oruk Anam	8,444	8,555	65%	60%	73%	64%	68%	59%
Akwa Ibom	Udung Uko	2,606	2,640	30%	26%	60%	53%	82%	71%
Akwa Ibom	Ukanafun	6,213	6,294	47%	43%	42%	34%	50%	42%
Akwa Ibom	Uruan	5,785	5,862	45%	40%	61%	56%	57%	52%
Akwa Ibom	Urue Offong/Oruko	3,480	3,526	61%	60%	109%	91%	129%	109%
Akwa Ibom	Uyo	15,139	15,339	41%	40%	70%	64%	77%	73%
Anambra	Aguata	20,416	20,814	57%	54%	96%	92%	105%	103%
Anambra	Anambra East	8,456	8,621	72%	67%	127%	123%	102%	102%
Anambra	Anambra West	9,233	9,413	60%	55%	87%	80%	75%	71%
Anambra	Anaocha	15,718	16,025	47%	44%	88%	89%	104%	103%
Anambra	Awka North	6,210	6,332	96%	87%	139%	133%	133%	129%
Anambra	Awka South	10,426	10,630	113%	104%	132%	118%	119%	110%
Anambra	Ayamelum	8,737	8,907	38%	33%	59%	54%	51%	47%
Anambra	Dunukofia	5,316	5,419	71%	62%	102%	99%	93%	84%
Anambra	Ekwusigo	8,727	8,897	82%	78%	120%	114%	120%	116%
Anambra	Idemili North	23,758	24,222	47%	44%	88%	87%	105%	108%
Anambra	Idemili South	11,454	11,677	69%	66%	82%	75%	79%	73%
Anambra	Ihiala	16,664	16,989	62%	61%	98%	119%	136%	134%
Anambra	Njikoka	8,188	8,348	65%	62%	106%	103%	102%	99%
Anambra	Nnewi North	8,690	8,860	76%	68%	104%	98%	99%	90%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Anambra	Nnewi South	12,887	13,138	56%	51%	79%	72%	78%	70%
Anambra	Ogbaru	12,237	12,476	81%	73%	119%	110%	83%	81%
Anambra	Onitsha North	6,891	7,025	69%	68%	126%	114%	109%	101%
Anambra	Onitsha South	7,537	7,684	93%	81%	154%	132%	148%	134%
Anambra	Orumba North	9,508	9,694	48%	47%	79%	75%	82%	77%
Anambra	Orumba South	10,324	10,526	44%	42%	63%	62%	56%	54%
Anambra	Oyi	9,267	9,448	60%	55%	96%	88%	90%	81%
Bauchi	Alkaleri	22,951	23,683	85%	78%	90%	85%	75%	70%
Bauchi	Bauchi	34,403	35,501	99%	90%	109%	105%	100%	96%
Bauchi	Bogoro	5,867	6,054	104%	102%	110%	104%	87%	83%
Bauchi	Damban	10,515	10,850	94%	84%	123%	116%	108%	97%
Bauchi	Darazo	17,529	18,088	90%	83%	103%	107%	91%	89%
Bauchi	Dass	6,266	6,466	109%	106%	115%	115%	88%	86%
Bauchi	Gamawa	19,952	20,589	71%	68%	90%	85%	84%	81%
Bauchi	Ganjuwa	19,540	20,163	126%	118%	133%	125%	122%	121%
Bauchi	Giade	10,936	11,285	94%	87%	98%	95%	83%	79%
Bauchi	Itas/Gadau	16,024	16,535	77%	70%	93%	87%	73%	72%
Bauchi	Jama'are	8,213	8,475	75%	70%	95%	93%	72%	70%
Bauchi	Katagum	20,620	21,278	88%	83%	88%	85%	78%	75%
Bauchi	Kirfi	10,284	10,613	79%	73%	104%	101%	86%	83%
Bauchi	Misau	18,357	18,943	71%	65%	81%	74%	67%	63%
Bauchi	Ningi	26,975	27,836	79%	72%	86%	80%	79%	72%
Bauchi	Shira	16,304	16,824	66%	60%	87%	76%	70%	70%
Bauchi	Tafawa-Balewa	15,326	15,815	97%	93%	104%	103%	93%	92%
Bauchi	Toro	24,412	25,191	121%	110%	143%	136%	131%	124%
Bauchi	Warji	7,992	8,247	88%	83%	101%	100%	85%	81%
Bauchi	Zaki	13,339	13,764	132%	121%	147%	139%	125%	120%
Bayelsa	Brass	10,664	10,858	40%	35%	90%	80%	114%	102%
Bayelsa	Ekeremor	15,575	15,857	64%	58%	102%	91%	108%	99%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Bayelsa	Kolokuma/Opokuma	4,454	4,535	15%	13%	37%	32%	87%	82%
Bayelsa	Nembe	7,546	7,682	45%	42%	79%	72%	106%	96%
Bayelsa	Ogbia	10,369	10,557	32%	28%	52%	47%	83%	76%
Bayelsa	Sagbama	10,785	10,981	24%	22%	42%	38%	85%	76%
Bayelsa	Southern Ijaw	18,408	18,741	25%	23%	49%	46%	56%	55%
Bayelsa	Yenegoa	20,363	20,732	58%	54%	71%	68%	66%	64%
Benue	Ado	10,084	10,278	88%	72%	67%	58%	119%	108%
Benue	Agatu	6,512	6,637	64%	59%	93%	84%	107%	98%
Benue	Apa	5,455	5,560	58%	48%	101%	90%	120%	113%
Benue	Buruku	11,484	11,705	51%	47%	84%	80%	94%	89%
Benue	Gboko	20,234	20,623	95%	90%	114%	104%	111%	104%
Benue	Guma	10,801	11,008	58%	52%	56%	46%	74%	68%
Benue	Gwer East	9,225	9,402	61%	54%	71%	67%	92%	85%
Benue	Gwer West	6,886	7,018	112%	99%	117%	102%	154%	123%
Benue	Katsina-Ala	12,668	12,911	55%	48%	66%	58%	73%	66%
Benue	Konshisha	12,722	12,966	37%	33%	60%	53%	54%	56%
Benue	Kwande	14,020	14,289	116%	101%	90%	78%	121%	108%
Benue	Logo	9,531	9,713	75%	74%	91%	92%	101%	104%
Benue	Makurdi	16,765	17,087	89%	90%	105%	112%	130%	133%
Benue	Obi	5,573	5,680	93%	87%	114%	108%	132%	123%
Benue	Ogbadibo	7,256	7,395	57%	56%	85%	84%	98%	95%
Benue	Ohimini	4,030	4,107	106%	98%	116%	108%	131%	116%
Benue	Oju	9,597	9,781	81%	74%	115%	101%	118%	109%
Benue	Okpokwu	9,958	10,149	59%	49%	38%	31%	66%	58%
Benue	Oturkpo	14,751	15,034	77%	71%	106%	103%	102%	95%
Benue	Tarka	4,481	4,567	59%	51%	90%	84%	113%	103%
Benue	Ukum	12,229	12,464	75%	68%	59%	54%	76%	66%
Benue	Ushongo	10,617	10,821	55%	49%	88%	75%	131%	118%
Benue	Vandeikya	12,972	13,222	52%	58%	51%	45%	70%	65%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Borno	Abadam	5,711	5,819	5%	1%	20%	14%	13%	12%
Borno	Askira/Uba	7,872	8,022	157%	147%	196%	184%	190%	181%
Borno	Bama	15,391	15,684	61%	55%	136%	125%	155%	150%
Borno	Bayo	4,502	4,588	154%	140%	220%	213%	212%	202%
Borno	Biu	10,037	10,228	197%	196%	203%	183%	165%	145%
Borno	Chibok	3,768	3,840	229%	178%	218%	215%	262%	269%
Borno	Damboa	13,201	13,452	74%	67%	98%	89%	139%	134%
Borno	Dikwa	6,038	6,152	94%	92%	84%	78%	94%	88%
Borno	Gubio	8,709	8,875	76%	70%	134%	126%	127%	111%
Borno	Guzamala	5,453	5,556	0%	0%	0%	0%	0%	0%
Borno	Gwoza	15,752	16,051	62%	55%	79%	71%	113%	111%
Borno	Hawul	6,859	6,989	108%	102%	130%	123%	133%	125%
Borno	Jere	12,040	12,269	193%	170%	318%	290%	338%	304%
Borno	Kaga	5,131	5,229	94%	91%	127%	122%	113%	106%
Borno	Kala/Balge	3,466	3,532	36%	29%	58%	55%	62%	61%
Borno	Konduga	8,925	9,095	107%	88%	160%	138%	220%	180%
Borno	Kukawa	11,622	11,843	41%	37%	61%	55%	53%	47%
Borno	Kwaya Kusar	3,221	3,282	305%	257%	369%	342%	399%	370%
Borno	Mafa	5,901	6,013	147%	134%	186%	172%	168%	133%
Borno	Magumeri	7,994	8,146	55%	46%	111%	101%	71%	65%
Borno	Maiduguri	29,729	30,294	72%	63%	115%	100%	129%	111%
Borno	Marte	7,375	7,515	6%	4%	11%	7%	9%	8%
Borno	Mobbar	6,650	6,776	48%	44%	69%	54%	87%	77%
Borno	Monguno	6,262	6,381	286%	245%	310%	260%	274%	232%
Borno	Ngala	13,515	13,772	55%	45%	80%	62%	88%	69%
Borno	Nganzai	5,689	5,797	94%	85%	130%	126%	148%	136%
Borno	Shani	5,833	5,944	164%	141%	200%	179%	188%	177%
Cross River	Abi	8,536	8,682	69%	67%	88%	86%	90%	83%
Cross River	Akamkpa	8,909	9,061	80%	77%	106%	100%	97%	93%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Cross River	Akpabuyo	15,998	16,272	51%	47%	77%	69%	75%	68%
Cross River	Bakassi	1,909	1,942	140%	131%	160%	143%	177%	149%
Cross River	Bekwarra	6,238	6,345	68%	64%	95%	89%	83%	79%
Cross River	Biase	9,973	10,144	81%	73%	104%	95%	95%	86%
Cross River	Boki	10,973	11,160	75%	73%	98%	95%	92%	87%
Cross River	Calabar Municipal	10,575	10,756	48%	42%	65%	57%	72%	64%
Cross River	Calabar South	11,296	11,489	81%	75%	103%	96%	92%	86%
Cross River	Etung	4,727	4,808	77%	72%	97%	94%	103%	106%
Cross River	Ikom	9,572	9,736	56%	50%	67%	64%	67%	64%
Cross River	Obanliku	6,503	6,615	77%	70%	102%	99%	84%	83%
Cross River	Obubra	10,165	10,339	64%	59%	92%	92%	80%	72%
Cross River	Obudu	9,438	9,599	60%	57%	83%	80%	78%	74%
Cross River	Odukpani	11,344	11,538	60%	55%	95%	92%	91%	85%
Cross River	Ogoja	10,133	10,307	72%	66%	90%	78%	78%	66%
Cross River	Yakurr	11,580	11,778	59%	56%	99%	98%	87%	82%
Cross River	Yala	12,429	12,641	65%	63%	87%	83%	85%	81%
Delta	Aniocha North	5,579	5,687	80%	74%	103%	91%	111%	102%
Delta	Aniocha South	7,491	7,637	78%	74%	106%	100%	94%	86%
Delta	Bomadi	4,616	4,706	62%	59%	99%	94%	94%	90%
Delta	Burutu	11,170	11,388	40%	32%	69%	60%	67%	60%
Delta	Ethiope East	10,698	10,906	68%	60%	120%	102%	136%	124%
Delta	Ethiope West	10,847	11,058	79%	75%	111%	106%	115%	106%
Delta	Ika North East	9,785	9,976	66%	57%	116%	104%	109%	99%
Delta	Ika South	8,663	8,831	56%	48%	91%	81%	111%	103%
Delta	Isoko North	7,680	7,830	72%	65%	121%	113%	131%	121%
Delta	Isoko South	12,132	12,368	40%	38%	86%	82%	91%	87%
Delta	Ndokwa East	5,497	5,604	42%	38%	67%	61%	78%	68%
Delta	Ndokwa West	7,956	8,111	43%	40%	85%	80%	86%	82%
Delta	Okpe	6,928	7,063	60%	56%	91%	84%	92%	90%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Delta	Oshimili North	6,144	6,263	87%	80%	131%	126%	127%	116%
Delta	Oshimili South	7,970	8,126	76%	63%	114%	100%	129%	107%
Delta	Patani	3,607	3,678	47%	41%	100%	88%	99%	89%
Delta	Sapele	9,158	9,336	48%	38%	80%	73%	87%	75%
Delta	Udu	7,638	7,787	66%	55%	99%	91%	91%	81%
Delta	Ughelli North	17,103	17,437	62%	51%	102%	89%	103%	93%
Delta	Ughelli South	11,379	11,601	57%	48%	79%	69%	79%	70%
Delta	Ukwuani	6,414	6,539	48%	46%	88%	80%	98%	93%
Delta	Uvwie	10,201	10,400	65%	59%	85%	77%	91%	81%
Delta	Warri North	7,315	7,458	47%	39%	93%	84%	96%	90%
Delta	Warri South	16,165	16,480	57%	50%	93%	86%	93%	83%
Delta	Warri South-West	6,216	6,338	49%	45%	88%	81%	75%	66%
Ebonyi	Abakaliki	8,814	9,031	91%	83%	123%	105%	108%	97%
Ebonyi	Afikpo North	9,098	9,322	75%	71%	100%	100%	97%	91%
Ebonyi	Afikpo South	9,124	9,350	50%	45%	97%	92%	98%	94%
Ebonyi	Ebonyi	7,368	7,550	133%	118%	151%	142%	144%	130%
Ebonyi	Ezza North	8,459	8,668	64%	61%	84%	84%	74%	72%
Ebonyi	Ezza South	7,738	7,929	66%	70%	75%	75%	84%	86%
Ebonyi	Ikwo	12,466	12,774	65%	61%	76%	74%	80%	71%
Ebonyi	Ishielu	8,774	8,991	98%	91%	105%	99%	94%	91%
Ebonyi	Ivo	7,024	7,198	81%	77%	111%	105%	99%	94%
Ebonyi	Izzi	13,597	13,933	86%	77%	116%	97%	133%	117%
Ebonyi	Ohaozara	8,634	8,847	59%	55%	103%	100%	109%	105%
Ebonyi	Ohaukwu	11,405	11,687	43%	39%	65%	58%	64%	61%
Ebonyi	Onicha	13,757	14,097	64%	58%	94%	88%	97%	91%
Edo	Akoko-Edo	15,106	15,436	58%	56%	67%	63%	67%	64%
Edo	Egor	19,590	20,017	47%	41%	55%	51%	48%	44%
Edo	Esan Central	6,069	6,202	44%	39%	41%	39%	50%	45%
Edo	Esan North-East	6,878	7,028	39%	36%	45%	41%	61%	55%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Edo	Esan South-East	9,666	9,877	67%	62%	57%	51%	42%	37%
Edo	Esan West	7,253	7,411	42%	40%	40%	37%	68%	64%
Edo	Etsako Central	5,451	5,570	63%	54%	99%	93%	109%	92%
Edo	Etsako East	8,414	8,598	41%	37%	43%	38%	46%	43%
Edo	Etsako West	11,389	11,637	43%	37%	66%	60%	68%	61%
Edo	Iguegben	4,014	4,101	29%	26%	41%	35%	67%	87%
Edo	Ikpoba-Okha	21,388	21,855	54%	52%	67%	57%	75%	72%
Edo	Oredo	21,594	22,064	44%	45%	66%	63%	68%	95%
Edo	Orhionmwon	10,531	10,760	17%	15%	22%	19%	69%	14%
Edo	Ovia North-East	8,867	9,060	56%	52%	69%	65%	74%	67%
Edo	Ovia South-West	7,801	7,971	56%	49%	58%	51%	57%	51%
Edo	Owan East	8,898	9,092	20%	18%	41%	38%	37%	34%
Edo	Owan West	5,613	5,735	36%	31%	40%	40%	49%	43%
Edo	Uhunmwonde	6,963	7,115	75%	70%	93%	88%	94%	87%
Ekiti	Ado-Ekiti	18,062	18,463	82%	78%	92%	91%	95%	94%
Ekiti	Efon	5,088	5,201	78%	76%	103%	101%	102%	99%
Ekiti	Ekiti East	8,074	8,253	37%	36%	78%	75%	111%	104%
Ekiti	Ekiti South-West	9,673	9,887	58%	55%	99%	94%	111%	104%
Ekiti	Ekiti West	10,528	10,762	43%	40%	79%	72%	93%	85%
Ekiti	Emure	5,494	5,616	75%	71%	101%	98%	110%	106%
Ekiti	Gbonyin	8,673	8,865	39%	39%	66%	63%	86%	85%
Ekiti	Ido-Osi	9,312	9,519	41%	37%	73%	70%	101%	98%
Ekiti	Ijero	12,957	13,245	46%	43%	92%	89%	95%	92%
Ekiti	Ikere	8,624	8,815	32%	32%	59%	57%	94%	91%
Ekiti	Ikole	9,857	10,076	30%	27%	55%	51%	76%	72%
Ekiti	Ilejemeje	2,548	2,604	40%	37%	87%	82%	114%	113%
Ekiti	Irepodun/Ifelodun	7,558	7,726	42%	40%	51%	49%	87%	85%
Ekiti	Ise/Orun	6,657	6,805	71%	66%	85%	79%	112%	105%
Ekiti	Moba	8,573	8,764	69%	63%	96%	94%	106%	101%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Ekiti	Oye	7,854	8,029	47%	45%	87%	83%	106%	97%
Enugu	Aninri	7,451	7,588	19%	17%	79%	81%	75%	68%
Enugu	Awgu	11,040	11,243	74%	71%	107%	104%	112%	108%
Enugu	Enugu East	15,551	15,837	72%	68%	117%	111%	100%	97%
Enugu	Enugu North	13,644	13,895	66%	76%	92%	85%	106%	99%
Enugu	Enugu South	11,073	11,277	19%	18%	95%	86%	93%	85%
Enugu	Ezeagu	9,457	9,631	109%	104%	114%	111%	115%	112%
Enugu	Igbo-Etiti	11,660	11,874	80%	77%	118%	104%	104%	95%
Enugu	Igbo-Eze-North	14,456	14,722	94%	83%	102%	92%	97%	87%
Enugu	Igbo-Eze-South	8,209	8,360	70%	66%	86%	79%	93%	82%
Enugu	Isi-Uzo	8,270	8,422	34%	33%	64%	62%	95%	93%
Enugu	Nkanu East	8,290	8,442	58%	51%	85%	76%	102%	90%
Enugu	Nkanu West	8,174	8,324	68%	61%	96%	90%	100%	92%
Enugu	Nsukka	17,253	17,571	49%	45%	86%	77%	96%	78%
Enugu	Oji-River	7,054	7,183	59%	55%	99%	103%	119%	111%
Enugu	Udenu	9,944	10,127	100%	91%	133%	122%	124%	112%
Enugu	Udi	13,039	13,279	63%	59%	83%	78%	90%	85%
Enugu	Uzo-Uwani	6,936	7,064	33%	31%	48%	46%	85%	76%
FCT, Abuja	Abaji	5,046	5,253	74%	71%	164%	163%	175%	168%
FCT, Abuja	Bwari	19,619	20,421	56%	55%	105%	106%	94%	93%
FCT, Abuja	Gwagwalada	13,623	14,180	62%	58%	124%	120%	113%	115%
FCT, Abuja	Kuje	8,407	8,751	79%	80%	140%	145%	132%	134%
FCT, Abuja	Kwali	7,412	7,715	57%	55%	136%	132%	140%	134%
FCT, Abuja	Municipal Area Council	67,225	69,974	37%	36%	75%	76%	78%	73%
Gombe	Akko	22,225	22,870	122%	110%	122%	118%	109%	107%
Gombe	Balanga	13,982	14,388	111%	108%	101%	97%	82%	82%
Gombe	Billiri	13,298	13,684	76%	71%	90%	81%	55%	53%
Gombe	Dukku	13,630	14,025	207%	187%	123%	113%	86%	83%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Gombe	Funakaye	15,531	15,981	150%	126%	122%	112%	83%	86%
Gombe	Gombe	17,630	18,142	159%	150%	152%	146%	138%	133%
Gombe	Kaltungo	9,855	10,141	100%	95%	86%	84%	72%	72%
Gombe	Kwami	12,848	13,220	114%	106%	129%	127%	104%	103%
Gombe	Nafada	9,090	9,354	72%	68%	91%	88%	64%	60%
Gombe	Shomgom	9,968	10,257	60%	56%	69%	67%	47%	46%
Gombe	Yamaltu/Deba	16,791	17,278	133%	127%	136%	126%	111%	110%
Imo	Aboh-Mbaise	10,499	10,686	46%	43%	56%	53%	64%	57%
Imo	Ahiazu-Mbaise	9,171	9,334	50%	48%	65%	60%	70%	66%
Imo	Ehime -Mbano	7,026	7,151	91%	86%	107%	103%	110%	105%
Imo	Ezinihitte	8,886	9,044	61%	54%	82%	73%	75%	66%
Imo	Ideato North	8,500	8,651	55%	51%	64%	59%	75%	70%
Imo	Ideato South	8,579	8,732	60%	55%	64%	60%	80%	73%
Imo	Ihitte/Uboma	6,479	6,594	107%	101%	130%	125%	128%	123%
Imo	Ikeduru	8,012	8,155	101%	91%	130%	120%	156%	134%
Imo	Isiala Mbano	10,664	10,854	99%	91%	120%	109%	119%	108%
Imo	Isu	8,825	8,982	41%	37%	49%	46%	71%	68%
Imo	Mbatoli	12,747	12,974	46%	42%	77%	66%	81%	71%
Imo	Ngor-Okpala	8,582	8,735	49%	45%	64%	63%	107%	97%
Imo	Njaba	7,787	7,925	57%	54%	73%	68%	71%	63%
Imo	Nkwerre	4,301	4,378	83%	76%	94%	88%	127%	117%
Imo	Nwangele	6,894	7,017	56%	51%	71%	63%	67%	60%
Imo	Obowo	6,338	6,451	83%	79%	119%	108%	105%	94%
Imo	Oguta	7,674	7,810	42%	39%	110%	104%	114%	108%
Imo	Ohaji/Egbema	9,795	9,969	65%	64%	74%	72%	87%	87%
Imo	Okigwe	7,096	7,222	47%	44%	81%	71%	101%	94%
Imo	Onuimo	5,326	5,420	53%	47%	126%	119%	122%	119%
Imo	Orlu	7,658	7,795	75%	70%	70%	66%	98%	92%
Imo	Orsu	6,439	6,554	37%	36%	26%	26%	42%	41%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Imo	Oru East	6,000	6,107	48%	46%	66%	62%	77%	70%
Imo	Oru West	6,305	6,417	55%	51%	98%	89%	111%	106%
Imo	Owerri Municipal	6,826	6,948	62%	57%	120%	109%	119%	111%
Imo	Owerri North	9,412	9,579	154%	143%	88%	84%	110%	91%
Imo	Owerri West	5,327	5,421	78%	70%	102%	93%	119%	111%
Jigawa	Auyo	8,941	9,241	91%	84%	109%	106%	89%	87%
Jigawa	Babura	14,095	14,569	128%	122%	109%	106%	93%	91%
Jigawa	Birnin Kudu	21,225	21,938	195%	194%	104%	87%	89%	82%
Jigawa	Birniwa	9,640	9,964	44%	40%	108%	97%	105%	100%
Jigawa	Buji	6,595	6,817	116%	105%	137%	124%	132%	127%
Jigawa	Dutse	16,672	17,232	123%	119%	122%	114%	105%	103%
Jigawa	Gagarawa	5,445	5,628	117%	113%	112%	107%	100%	101%
Jigawa	Garki	10,311	10,657	142%	134%	117%	113%	109%	104%
Jigawa	Gumel	7,258	7,502	92%	88%	85%	82%	100%	97%
Jigawa	Guri	7,790	8,052	99%	87%	99%	86%	85%	82%
Jigawa	Gwaram	18,462	19,083	117%	108%	102%	95%	99%	92%
Jigawa	Gwiwa	8,434	8,717	97%	93%	95%	90%	109%	91%
Jigawa	Hadejia	7,154	7,395	88%	85%	106%	102%	101%	95%
Jigawa	Jahun	15,517	16,038	119%	112%	101%	95%	88%	85%
Jigawa	Kafin Hausa	18,359	18,976	80%	75%	102%	92%	101%	99%
Jigawa	Kaugama	8,667	8,958	120%	118%	115%	110%	94%	91%
Jigawa	Kazaure	10,938	11,306	110%	106%	104%	97%	100%	96%
Jigawa	Kiri Kasamma	12,972	13,408	102%	98%	84%	78%	92%	86%
Jigawa	Kiyawa	11,712	12,105	160%	157%	142%	138%	119%	115%
Jigawa	Maigatari	12,172	12,581	114%	112%	104%	100%	97%	92%
Jigawa	Malam Madori	10,933	11,300	96%	89%	92%	84%	81%	76%
Jigawa	Miga	8,698	8,991	129%	125%	113%	111%	101%	99%
Jigawa	Ringim	13,006	13,443	145%	136%	115%	108%	107%	103%
Jigawa	Roni	5,271	5,448	133%	128%	132%	128%	122%	119%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Jigawa	Sule Tankarkar	8,863	9,160	126%	121%	122%	119%	111%	108%
Jigawa	Taura	8,924	9,224	129%	131%	109%	103%	104%	99%
Jigawa	Yankwashi	6,486	6,704	119%	114%	100%	93%	87%	83%
Kaduna	Birnin Gwari	14,628	15,013	131%	122%	146%	136%	134%	129%
Kaduna	Chikun	21,345	21,907	66%	63%	91%	89%	88%	83%
Kaduna	Giwa	16,603	17,039	127%	117%	167%	155%	178%	159%
Kaduna	Igabi	24,938	25,594	103%	96%	142%	134%	119%	109%
Kaduna	Ikara	11,241	11,536	147%	137%	181%	167%	208%	205%
Kaduna	Jaba	9,006	9,243	63%	60%	76%	74%	98%	94%
Kaduna	Jema'A	16,157	16,582	49%	45%	70%	65%	76%	72%
Kaduna	Kachia	14,159	14,532	65%	63%	95%	93%	112%	111%
Kaduna	Kaduna North	20,733	21,279	58%	53%	69%	63%	73%	65%
Kaduna	Kaduna South	23,324	23,938	58%	51%	75%	67%	94%	87%
Kaduna	Kagarko	13,966	14,333	76%	73%	84%	82%	101%	98%
Kaduna	Kajuru	6,426	6,595	86%	85%	116%	117%	132%	127%
Kaduna	Kaura	12,902	13,241	93%	92%	88%	87%	93%	89%
Kaduna	Kauru	9,854	10,114	138%	129%	158%	142%	144%	135%
Kaduna	Kubau	16,348	16,778	118%	112%	164%	154%	133%	122%
Kaduna	Kudan	8,057	8,268	98%	91%	148%	138%	122%	122%
Kaduna	Lere	19,195	19,700	140%	127%	198%	173%	249%	229%
Kaduna	Makarfi	8,478	8,701	150%	140%	199%	188%	167%	162%
Kaduna	Sabon Gari	16,628	17,066	139%	134%	178%	173%	140%	133%
Kaduna	Sanga	8,656	8,884	94%	90%	119%	113%	124%	119%
Kaduna	Soba	16,999	17,446	138%	132%	167%	152%	160%	151%
Kaduna	Zangon Kataf	18,338	18,820	79%	75%	104%	99%	99%	95%
Kaduna	Zaria	23,661	24,283	110%	100%	140%	131%	129%	122%
Kano	Ajingi	11,189	11,482	96%	91%	104%	97%	82%	78%
Kano	Albasu	12,218	12,539	97%	92%	111%	106%	96%	93%
Kano	Bagwai	10,464	10,738	79%	75%	100%	93%	87%	86%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Kano	Bebeji	12,135	12,453	99%	97%	104%	100%	100%	95%
Kano	Bichi	17,805	18,272	87%	81%	99%	93%	91%	87%
Kano	Bunkure	10,981	11,268	95%	90%	107%	102%	110%	103%
Kano	Dala	26,909	27,614	86%	82%	95%	92%	80%	77%
Kano	Dambatta	13,363	13,713	92%	87%	113%	107%	96%	92%
Kano	Dawakin Kudu	14,483	14,862	95%	93%	105%	102%	94%	90%
Kano	Dawakin Tofa	15,927	16,345	86%	82%	101%	97%	84%	82%
Kano	Doguwa	9,714	9,969	113%	106%	121%	110%	115%	109%
Kano	Fagge	12,776	13,111	105%	99%	100%	94%	97%	92%
Kano	Gabasawa	13,562	13,917	95%	94%	102%	96%	92%	88%
Kano	Garko	10,442	10,715	97%	93%	94%	90%	88%	85%
Kano	Garum Mallam	7,485	7,682	94%	90%	99%	94%	92%	91%
Kano	Gaya	12,916	13,255	90%	87%	112%	102%	86%	82%
Kano	Gezawa	18,125	18,599	97%	93%	101%	96%	89%	85%
Kano	Gwale	23,264	23,874	94%	91%	101%	98%	96%	91%
Kano	Gwarzo	11,822	12,132	87%	82%	125%	119%	103%	102%
Kano	Kabo	9,884	10,143	99%	95%	101%	99%	79%	78%
Kano	Kano Municipal	23,487	24,102	93%	92%	105%	104%	82%	81%
Kano	Karaye	9,086	9,324	81%	77%	99%	90%	93%	91%
Kano	Kibiya	8,786	9,016	93%	88%	101%	95%	89%	84%
Kano	Kiru	17,014	17,459	104%	100%	111%	106%	109%	105%
Kano	Kumbotso	19,018	19,517	99%	95%	126%	122%	126%	124%
Kano	Kunchi	7,134	7,320	99%	93%	115%	104%	96%	89%
Kano	Kura	9,291	9,535	87%	83%	106%	100%	83%	82%
Kano	Madobi	8,779	9,009	88%	85%	107%	103%	88%	90%
Kano	Makoda	14,290	14,665	88%	84%	92%	88%	80%	78%
Kano	Minjibir	13,738	14,097	92%	76%	101%	95%	80%	73%
Kano	Nassarawa	38,339	39,344	88%	89%	126%	103%	71%	67%
Kano	Rano	9,345	9,590	94%	89%	100%	95%	99%	93%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Kano	Rimin Gado	6,733	6,910	86%	82%	110%	106%	97%	94%
Kano	Rogo	14,634	15,017	90%	88%	101%	95%	110%	108%
Kano	Shanono	9,035	9,272	82%	77%	108%	104%	103%	102%
Kano	Sumaila	16,299	16,726	101%	95%	108%	99%	113%	109%
Kano	Takai	13,027	13,369	110%	103%	118%	107%	135%	126%
Kano	Tarauni	14,224	14,597	87%	84%	107%	104%	108%	104%
Kano	Tofa	6,280	6,445	83%	83%	94%	94%	86%	84%
Kano	Tsanyawa	10,132	10,397	85%	80%	110%	107%	90%	86%
Kano	Tudun Wada	14,891	15,281	101%	96%	99%	92%	96%	91%
Kano	Ungogo	23,753	24,375	100%	96%	115%	109%	114%	107%
Kano	Warawa	8,275	8,492	100%	97%	104%	98%	84%	87%
Kano	Wudil	11,899	12,211	113%	109%	124%	117%	93%	91%
Katsina	Bakori	10,527	10,907	167%	163%	166%	152%	156%	153%
Katsina	Batagarawa	13,008	13,477	70%	69%	97%	91%	96%	94%
Katsina	Batsari	14,728	15,259	69%	64%	94%	89%	104%	99%
Katsina	Baure	13,913	14,416	85%	87%	85%	79%	86%	84%
Katsina	Bindawa	10,737	11,125	74%	67%	100%	79%	93%	79%
Katsina	Charanchi	9,698	10,048	91%	78%	114%	102%	124%	109%
Katsina	Dan Musa	8,012	8,302	76%	69%	90%	84%	92%	89%
Katsina	Dandume	10,271	10,642	98%	93%	123%	112%	181%	166%
Katsina	Danja	8,859	9,179	153%	131%	194%	207%	159%	150%
Katsina	Daura	15,485	16,044	55%	51%	57%	56%	135%	91%
Katsina	Dutsi	8,458	8,764	104%	97%	85%	80%	85%	79%
Katsina	Dutsin Ma	11,957	12,389	142%	135%	117%	120%	109%	102%
Katsina	Faskari	13,815	14,314	81%	75%	84%	75%	104%	92%
Katsina	Funtua	15,897	16,471	106%	94%	141%	125%	136%	130%
Katsina	Ingawa	11,963	12,395	79%	88%	75%	73%	73%	70%
Katsina	Jibia	11,963	12,395	76%	64%	82%	70%	105%	96%
Katsina	Kafur	14,298	14,814	120%	112%	127%	112%	92%	87%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Katsina	Kaita	12,995	13,465	115%	102%	107%	102%	92%	92%
Katsina	Kankara	17,318	17,943	76%	67%	80%	72%	71%	65%
Katsina	Kankia	10,672	11,057	89%	74%	97%	88%	89%	86%
Katsina	Katsina	22,443	23,253	86%	77%	97%	87%	99%	92%
Katsina	Kurfi	8,286	8,586	86%	79%	88%	82%	127%	117%
Katsina	Kusada	6,996	7,248	125%	119%	107%	98%	113%	100%
Katsina	Mai'Adua	14,178	14,690	61%	55%	60%	57%	59%	55%
Katsina	Malumfashi	12,891	13,356	134%	112%	124%	111%	113%	111%
Katsina	Mani	12,471	12,922	80%	69%	100%	91%	85%	82%
Katsina	Mashi	12,201	12,642	84%	77%	101%	92%	91%	91%
Katsina	Matazu	8,127	8,421	100%	94%	121%	114%	121%	116%
Katsina	Musawa	12,101	12,538	102%	89%	94%	86%	79%	77%
Katsina	Rimi	10,835	11,226	91%	89%	110%	105%	109%	110%
Katsina	Sabuwa	9,588	9,934	69%	54%	80%	73%	90%	83%
Katsina	Safana	12,952	13,419	71%	63%	90%	84%	115%	107%
Katsina	Sandamu	9,675	10,024	69%	59%	75%	72%	67%	65%
Katsina	Zango	10,905	11,299	57%	53%	58%	56%	71%	69%
Kebbi	Aleiro	4,461	4,620	120%	112%	129%	118%	83%	84%
Kebbi	Arewa Dandi	12,443	12,887	64%	62%	83%	75%	82%	79%
Kebbi	Argungu	13,217	13,689	122%	114%	111%	108%	96%	96%
Kebbi	Augie	7,930	8,213	56%	59%	100%	92%	82%	80%
Kebbi	Bagudo	16,080	16,654	82%	78%	108%	101%	114%	107%
Kebbi	Birnin Kebbi	18,149	18,797	85%	92%	109%	113%	96%	94%
Kebbi	Bunza	8,212	8,506	81%	76%	99%	96%	96%	91%
Kebbi	Dandi	9,755	10,103	61%	60%	100%	92%	86%	78%
Kebbi	Fakai	8,196	8,488	94%	82%	101%	98%	103%	99%
Kebbi	Gwandu	10,211	10,576	81%	84%	128%	124%	91%	91%
Kebbi	Jega	13,073	13,540	86%	81%	94%	82%	92%	85%
Kebbi	Kalgo	5,774	5,981	110%	92%	122%	109%	84%	77%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Kebbi	Koko/Besse	10,453	10,827	100%	94%	117%	104%	104%	97%
Kebbi	Maiyama	11,879	12,303	108%	98%	118%	102%	71%	71%
Kebbi	Ngaski	8,436	8,737	92%	96%	102%	109%	97%	101%
Kebbi	Sakaba	6,081	6,298	111%	107%	119%	114%	123%	119%
Kebbi	Shanga	8,597	8,904	107%	102%	118%	115%	133%	127%
Kebbi	Suru	10,158	10,520	67%	63%	79%	70%	74%	72%
Kebbi	Wasagu/Danko	17,931	18,572	62%	57%	78%	72%	88%	80%
Kebbi	Yauri	6,746	6,987	94%	88%	101%	97%	104%	98%
Kebbi	Zuru	11,193	11,593	95%	90%	98%	96%	102%	98%
Kogi	Adavi	10,724	10,985	90%	85%	147%	137%	130%	122%
Kogi	Ajaokuta	6,487	6,646	69%	68%	76%	71%	87%	82%
Kogi	Ankpa	14,180	14,525	71%	60%	79%	67%	111%	99%
Kogi	Bassa	7,425	7,606	43%	39%	66%	65%	60%	55%
Kogi	Dekina	13,806	14,143	50%	47%	89%	84%	97%	90%
Kogi	Ibaji	6,796	6,961	39%	35%	69%	63%	67%	59%
Kogi	Idah	4,233	4,336	136%	130%	227%	210%	161%	149%
Kogi	Igalamela-Odolu	7,850	8,042	66%	58%	107%	100%	92%	82%
Kogi	Ijumu	6,361	6,516	72%	72%	112%	113%	111%	111%
Kogi	Kabba/Bunu	7,714	7,902	62%	58%	104%	104%	103%	101%
Kogi	Kogi	6,147	6,297	33%	32%	57%	54%	66%	63%
Kogi	Lokoja	10,356	10,609	59%	52%	87%	85%	76%	74%
Kogi	Mopa-Muro	2,336	2,393	101%	102%	160%	161%	120%	121%
Kogi	Ofu	10,192	10,441	31%	27%	72%	71%	75%	73%
Kogi	Ogori/Magongo	2,101	2,153	74%	70%	94%	90%	113%	107%
Kogi	Okehi	10,607	10,866	99%	93%	123%	113%	121%	103%
Kogi	Okene	16,986	17,400	92%	91%	120%	113%	120%	117%
Kogi	Olamaboro	8,494	8,701	63%	50%	67%	52%	116%	94%
Kogi	Omala	5,749	5,890	73%	64%	108%	105%	79%	75%
Kogi	Yagba East	7,904	8,097	113%	109%	130%	125%	98%	95%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Kogi	Yagba West	7,433	7,614	48%	48%	127%	126%	125%	123%
Kwara	Asa	7,403	7,616	86%	94%	119%	117%	120%	118%
Kwara	Baruten	12,264	12,617	48%	37%	83%	69%	95%	87%
Kwara	Edu	11,796	12,136	90%	91%	84%	80%	85%	79%
Kwara	Ekiti	3,211	3,304	94%	90%	95%	93%	117%	109%
Kwara	Ifelodun	12,064	12,411	59%	51%	79%	66%	91%	88%
Kwara	Ilorin East	11,962	12,307	55%	47%	63%	56%	93%	89%
Kwara	Ilorin South	12,219	12,571	112%	98%	113%	107%	104%	99%
Kwara	Ilorin West	21,351	21,966	77%	69%	99%	93%	103%	101%
Kwara	Irepodun	8,701	8,952	89%	82%	94%	86%	95%	88%
Kwara	Isin	3,498	3,598	91%	91%	106%	106%	112%	108%
Kwara	Kaiama	7,270	7,479	93%	86%	108%	96%	116%	105%
Kwara	Moro	6,370	6,553	65%	60%	110%	113%	121%	126%
Kwara	Offa	5,250	5,402	85%	78%	94%	95%	98%	97%
Kwara	Oke Ero	3,374	3,471	73%	69%	83%	80%	114%	111%
Kwara	Oyun	5,518	5,677	93%	83%	108%	98%	105%	98%
Kwara	Pategi	6,576	6,765	89%	78%	79%	70%	101%	92%
Lagos	Agege	26,624	27,096	65%	62%	97%	100%	101%	95%
Lagos	Ajeromi/Ifelodun	39,601	40,301	89%	92%	116%	118%	106%	108%
Lagos	Alimosho	73,963	75,272	62%	60%	85%	92%	87%	85%
Lagos	Amuwo Odofin	18,418	18,744	53%	54%	87%	91%	95%	93%
Lagos	Apapa	12,582	12,805	86%	79%	102%	97%	102%	100%
Lagos	Badagry	13,956	14,203	81%	83%	105%	106%	89%	88%
Lagos	Epe	10,501	10,687	104%	104%	113%	115%	97%	97%
Lagos	Eti Osa	16,659	16,954	77%	80%	100%	110%	88%	93%
Lagos	Ibeju Lekki	6,801	6,921	114%	105%	140%	140%	132%	128%
Lagos	Ifako/Ijaye	24,768	25,207	61%	63%	100%	103%	106%	106%
Lagos	Ikeja	18,130	18,451	87%	83%	114%	111%	102%	97%
Lagos	Ikorodu	31,005	31,554	73%	73%	100%	108%	93%	100%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Lagos	Kosofe	38,517	39,199	69%	71%	87%	91%	88%	86%
Lagos	Lagos Island	12,124	12,338	63%	66%	78%	83%	83%	85%
Lagos	Lagos Mainland	18,392	18,717	61%	67%	74%	83%	78%	87%
Lagos	Mushin	36,643	37,291	60%	61%	86%	90%	88%	91%
Lagos	Ojo	34,620	35,233	72%	70%	105%	110%	91%	99%
Lagos	Oshodi/Isolo	35,977	36,614	81%	80%	109%	108%	87%	86%
Lagos	Shomolu	23,309	23,722	75%	70%	113%	105%	96%	94%
Lagos	Surulere	29,173	29,690	84%	82%	99%	99%	80%	81%
Nasarawa	Akwanga	6,883	7,095	73%	73%	69%	69%	77%	77%
Nasarawa	Awe	6,831	7,042	122%	117%	125%	121%	115%	109%
Nasarawa	Doma	8,471	8,733	86%	79%	91%	87%	92%	86%
Nasarawa	Karu	12,468	12,853	166%	155%	204%	195%	206%	197%
Nasarawa	Keana	4,809	4,957	95%	85%	92%	88%	96%	91%
Nasarawa	Keffi	5,623	5,796	139%	128%	140%	132%	146%	134%
Nasarawa	Kokona	6,659	6,865	93%	87%	94%	92%	96%	96%
Nasarawa	Lafia	20,067	20,687	120%	110%	130%	118%	116%	106%
Nasarawa	Nasarawa	11,519	11,874	105%	93%	110%	100%	112%	105%
Nasarawa	Nasarawa Egon	9,049	9,328	108%	104%	111%	106%	113%	110%
Nasarawa	Obi	9,033	9,312	149%	134%	136%	136%	115%	113%
Nasarawa	Toto	7,225	7,448	75%	76%	81%	80%	76%	75%
Nasarawa	Wamba	4,423	4,560	84%	83%	98%	95%	102%	102%
Niger	Agaie	8,914	9,162	128%	121%	151%	144%	146%	136%
Niger	Agwara	3,851	3,958	157%	144%	247%	242%	271%	263%
Niger	Bida	12,621	12,972	102%	98%	118%	113%	112%	110%
Niger	Borgu	11,533	11,854	135%	117%	153%	144%	144%	132%
Niger	Bosso	9,883	10,158	101%	84%	118%	107%	115%	103%
Niger	Chanchaga	13,509	13,885	116%	83%	107%	85%	99%	81%
Niger	Edati	10,752	11,051	107%	105%	105%	102%	103%	100%
Niger	Gbako	8,549	8,786	89%	86%	141%	138%	160%	147%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Niger	Gurara	6,101	6,271	100%	93%	125%	119%	103%	98%
Niger	Katcha	8,194	8,422	100%	99%	143%	151%	132%	131%
Niger	Kontagora	10,190	10,474	92%	82%	125%	115%	139%	126%
Niger	Lapai	7,386	7,591	107%	97%	141%	141%	156%	158%
Niger	Lavun	14,079	14,470	106%	105%	137%	127%	116%	115%
Niger	Magama	12,183	12,522	63%	55%	89%	88%	112%	99%
Niger	Mariga	13,375	13,747	70%	65%	105%	102%	112%	105%
Niger	Mashegu	14,421	14,822	58%	50%	104%	90%	99%	93%
Niger	Mokwa	16,427	16,884	103%	100%	120%	116%	121%	117%
Niger	Munya	6,952	7,145	74%	66%	114%	109%	118%	117%
Niger	Paikoro	10,602	10,897	80%	68%	93%	86%	94%	91%
Niger	Rafi	12,201	12,541	66%	63%	89%	82%	92%	85%
Niger	Rijau	11,807	12,136	72%	64%	107%	99%	115%	107%
Niger	Shiroro	15,788	16,227	85%	79%	100%	94%	96%	87%
Niger	Suleja	14,525	14,929	66%	59%	84%	80%	99%	100%
Niger	Tafa	5,603	5,759	92%	83%	144%	147%	121%	121%
Niger	Wushishi	5,485	5,637	74%	64%	92%	85%	104%	104%
Ogun	Abeokuta North	13,387	13,690	63%	56%	86%	76%	85%	75%
Ogun	Abeokuta South	16,642	17,018	57%	48%	72%	67%	87%	78%
Ogun	Ado Odo/Ota	35,014	35,805	50%	46%	71%	66%	74%	67%
Ogun	Ewekoro	3,668	3,750	21%	19%	90%	80%	96%	78%
Ogun	Ifo	34,899	35,688	203%	201%	74%	69%	87%	82%
Ogun	Ijebu East	7,328	7,493	157%	148%	87%	80%	89%	84%
Ogun	Ijebu North	18,907	19,334	36%	35%	87%	84%	91%	88%
Ogun	Ijebu North East	3,984	4,074	56%	49%	116%	113%	128%	125%
Ogun	Ijebu Ode	10,242	10,474	49%	47%	105%	100%	102%	95%
Ogun	Ikenne	7,895	8,074	155%	150%	95%	90%	98%	93%
Ogun	Imeko Afon	5,467	5,591	35%	33%	96%	93%	100%	92%
Ogun	Ipokia	10,003	10,229	78%	64%	67%	55%	57%	46%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Ogun	Obafemi Owode	15,218	15,561	156%	141%	67%	64%	84%	78%
Ogun	Odeda	7,278	7,442	52%	49%	87%	80%	94%	88%
Ogun	Odogbolu	8,453	8,644	45%	41%	80%	78%	96%	92%
Ogun	Ogun Waterside	4,850	4,959	56%	52%	84%	80%	92%	88%
Ogun	Remo North	4,497	4,599	32%	31%	84%	80%	95%	89%
Ogun	Shagamu	16,851	17,232	298%	287%	89%	84%	95%	86%
Ogun	Yewa North	12,091	12,364	218%	213%	82%	82%	96%	94%
Ogun	Yewa South	11,228	11,481	48%	45%	71%	68%	77%	73%
Ondo	Akoko North East	10,525	10,757	53%	51%	72%	72%	77%	76%
Ondo	Akoko North West	12,828	13,111	52%	51%	61%	60%	62%	60%
Ondo	Akoko South East	4,946	5,055	69%	69%	74%	73%	76%	75%
Ondo	Akoko South West	13,770	14,073	39%	38%	56%	54%	49%	48%
Ondo	Akure North	7,896	8,069	117%	115%	141%	139%	135%	133%
Ondo	Akure South	21,194	21,660	100%	96%	124%	122%	100%	96%
Ondo	Ese Odo	9,299	9,504	96%	93%	97%	94%	96%	94%
Ondo	Idanre	7,742	7,912	94%	88%	99%	94%	100%	92%
Ondo	Ifedore	10,580	10,813	21%	20%	24%	23%	23%	22%
Ondo	Ilaje	17,438	17,822	101%	96%	106%	99%	112%	105%
Ondo	Ile Oluji/Okeigbo	10,373	10,601	91%	89%	97%	94%	96%	93%
Ondo	Irele	8,711	8,902	79%	76%	111%	105%	107%	102%
Ondo	Odigbo	13,822	14,126	176%	170%	203%	198%	154%	149%
Ondo	Okitipupa	14,015	14,323	88%	84%	114%	109%	98%	94%
Ondo	Ondo East	4,486	4,584	83%	82%	89%	88%	84%	82%
Ondo	Ondo West	17,021	17,396	79%	75%	90%	87%	89%	87%
Ondo	Ose	8,695	8,886	43%	42%	46%	45%	47%	47%
Ondo	Owo	13,134	13,423	53%	51%	62%	61%	59%	59%
Osun	Atakunmosa East	3,808	3,865	21%	20%	64%	60%	120%	113%
Osun	Atakunmosa West	3,430	3,482	60%	58%	97%	92%	104%	93%
Osun	Ayedade	7,516	7,628	152%	145%	123%	121%	112%	112%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Osun	Ayedire	3,790	3,847	51%	49%	75%	71%	74%	70%
Osun	Boluwaduro	3,537	3,590	57%	53%	93%	88%	125%	117%
Osun	Boripe	6,964	7,069	72%	65%	130%	126%	110%	108%
Osun	Ede North	4,189	4,252	66%	62%	95%	92%	119%	109%
Osun	Ede South	3,800	3,857	67%	61%	112%	103%	105%	100%
Osun	Egbedore	3,720	3,776	72%	64%	96%	88%	98%	91%
Osun	Ejigbo	6,629	6,728	54%	48%	81%	77%	94%	98%
Osun	Ife Central	8,358	8,484	57%	56%	87%	81%	143%	139%
Osun	Ife East	9,400	9,541	70%	66%	113%	108%	138%	132%
Osun	Ife North	7,681	7,796	69%	64%	97%	93%	110%	107%
Osun	Ife South	6,763	6,865	67%	60%	97%	94%	108%	105%
Osun	Ifedayo	1,852	1,880	66%	79%	92%	109%	86%	89%
Osun	Ifelodun	4,835	4,907	81%	71%	108%	99%	98%	91%
Osun	Ila	3,101	3,147	67%	61%	118%	109%	124%	110%
Osun	Ilesha East	5,327	5,406	37%	34%	101%	95%	104%	94%
Osun	Ilesha West	5,175	5,253	64%	48%	122%	106%	82%	78%
Osun	Irepodun	5,972	6,061	59%	54%	76%	71%	95%	86%
Osun	Irewole	7,176	7,284	48%	43%	98%	93%	93%	92%
Osun	Isokan	5,156	5,234	32%	33%	63%	59%	141%	121%
Osun	Iwo	9,564	9,707	66%	62%	80%	77%	93%	85%
Osun	Obokun	5,823	5,910	64%	66%	80%	78%	75%	72%
Osun	Odo Otin	6,702	6,803	87%	81%	113%	106%	115%	106%
Osun	Ola Oluwa	3,828	3,885	34%	28%	60%	52%	79%	66%
Osun	Olorunda	6,585	6,683	49%	45%	83%	71%	82%	77%
Osun	Oriade	7,427	7,538	32%	30%	67%	66%	94%	91%
Osun	Orolu	5,151	5,228	56%	53%	78%	75%	86%	83%
Osun	Osogbo	7,831	7,948	69%	65%	95%	90%	116%	108%
Oyo	Afijio	7,414	7,558	66%	60%	94%	88%	96%	88%
Oyo	Akinyele	11,679	11,906	50%	49%	104%	98%	89%	85%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Oyo	Atiba	9,377	9,559	62%	57%	94%	86%	79%	73%
Oyo	Atisbo	6,122	6,241	56%	56%	50%	46%	54%	49%
Oyo	Egbeda	15,559	15,861	66%	63%	107%	104%	98%	96%
Oyo	Ibadan North	16,952	17,281	63%	56%	61%	57%	55%	53%
Oyo	Ibadan North East	18,257	18,611	69%	62%	105%	95%	110%	98%
Oyo	Ibadan North West	8,445	8,609	78%	74%	109%	101%	103%	93%
Oyo	Ibadan South East	14,701	14,986	53%	50%	75%	70%	80%	72%
Oyo	Ibadan South West	15,615	15,918	72%	65%	78%	72%	75%	70%
Oyo	Ibarapa Central	5,690	5,801	59%	56%	74%	67%	89%	81%
Oyo	Ibarapa East	6,533	6,659	75%	68%	91%	85%	114%	106%
Oyo	Ibarapa North	5,586	5,694	53%	43%	66%	55%	75%	67%
Oyo	Ido	5,706	5,817	73%	67%	126%	114%	121%	101%
Oyo	Irepo	6,772	6,903	70%	66%	109%	105%	110%	104%
Oyo	Iseyin	14,197	14,472	51%	47%	69%	64%	77%	70%
Oyo	Itesiwaju	7,109	7,247	44%	37%	74%	66%	136%	121%
Oyo	Iwajowa	5,690	5,801	61%	57%	96%	89%	84%	75%
Oyo	Kajola	11,106	11,322	58%	55%	68%	63%	79%	67%
Oyo	Lagelu	8,176	8,334	87%	85%	101%	97%	97%	91%
Oyo	Ogbomosho North	10,981	11,194	52%	51%	100%	99%	86%	81%
Oyo	Ogbomosho South	5,571	5,679	44%	41%	75%	72%	80%	77%
Oyo	Ogo Oluwa	3,602	3,672	60%	57%	111%	109%	117%	110%
Oyo	Olorunsogo	4,518	4,605	75%	68%	113%	109%	109%	101%
Oyo	Oluyole	11,202	11,419	76%	75%	108%	103%	105%	96%
Oyo	Ona ara	14,646	14,930	53%	51%	89%	86%	78%	75%
Oyo	Orelope	5,771	5,883	66%	62%	113%	108%	105%	101%
Oyo	Ori Ire	8,323	8,485	59%	53%	99%	91%	95%	88%
Oyo	Oyo East	6,843	6,976	78%	73%	117%	107%	100%	90%
Oyo	Oyo West	7,528	7,674	61%	57%	101%	95%	94%	89%
Oyo	Saki East	6,091	6,209	90%	81%	93%	87%	74%	63%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Oyo	Saki West	15,361	15,659	44%	43%	66%	60%	73%	56%
Oyo	Surulere	7,850	8,003	48%	40%	68%	60%	72%	65%
Plateau	Barkin Ladi	10,109	10,340	99%	100%	81%	80%	90%	86%
Plateau	Bassa	10,778	11,024	78%	72%	78%	71%	89%	80%
Plateau	Bokkos	10,293	10,528	69%	67%	59%	55%	64%	61%
Plateau	Jos East	4,937	5,050	71%	68%	65%	64%	77%	76%
Plateau	Jos North	24,762	25,326	67%	61%	68%	61%	84%	81%
Plateau	Jos South	17,691	18,094	79%	76%	60%	59%	75%	71%
Plateau	Kanam	9,569	9,787	117%	97%	103%	88%	129%	114%
Plateau	Kanke	7,004	7,163	60%	53%	47%	41%	54%	50%
Plateau	Langtang North	8,112	8,297	65%	56%	60%	52%	97%	88%
Plateau	Langtang South	6,132	6,271	69%	61%	63%	53%	67%	59%
Plateau	Mangu	17,011	17,399	81%	74%	63%	56%	63%	58%
Plateau	Mikang	5,619	5,747	69%	55%	56%	49%	68%	58%
Plateau	Pankshin	11,056	11,308	53%	50%	48%	45%	53%	51%
Plateau	Qua'an Pan	11,359	11,618	76%	64%	95%	84%	112%	100%
Plateau	Riyom	7,588	7,761	73%	72%	57%	55%	58%	56%
Plateau	Shendam	11,998	12,272	77%	66%	81%	69%	119%	107%
Plateau	Wase	9,327	9,540	69%	58%	78%	62%	100%	80%
Rivers	Abua/Odual	15,808	16,116	49%	45%	78%	72%	100%	95%
Rivers	Ahoada East	9,315	9,496	75%	72%	86%	82%	94%	90%
Rivers	Ahoada West	13,933	14,205	63%	57%	80%	73%	95%	79%
Rivers	Akuku Toru	8,715	8,885	43%	39%	58%	52%	78%	72%
Rivers	Andoni	11,787	12,017	97%	92%	101%	92%	108%	102%
Rivers	Asari-Toru	12,295	12,535	40%	36%	59%	55%	91%	87%
Rivers	Bonny	12,030	12,265	48%	52%	64%	59%	76%	71%
Rivers	Degema	13,952	14,225	80%	76%	92%	88%	101%	95%
Rivers	Eleme	10,663	10,871	71%	64%	97%	90%	103%	96%
Rivers	Emuoha	11,278	11,498	70%	66%	85%	81%	75%	71%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Rivers	Etche	13,935	14,206	74%	68%	89%	82%	100%	92%
Rivers	Gokana	12,782	13,032	96%	93%	135%	128%	132%	123%
Rivers	Ikwerre	10,598	10,805	79%	72%	98%	89%	90%	83%
Rivers	Khana	16,435	16,756	85%	80%	118%	111%	94%	89%
Rivers	Obio/Akpor	25,963	26,470	95%	88%	107%	100%	115%	106%
Rivers	Ogba/Egbema/Ndoni	15,865	16,174	56%	53%	83%	75%	119%	110%
Rivers	Ogu Bolo	4,172	4,253	107%	101%	117%	111%	117%	113%
Rivers	Okrika	12,402	12,644	87%	85%	120%	114%	127%	121%
Rivers	Omumma	5,606	5,716	114%	108%	121%	109%	114%	105%
Rivers	Opobo/Nkoro	8,463	8,628	85%	80%	122%	116%	117%	109%
Rivers	Oyigbo	6,853	6,987	69%	65%	104%	103%	104%	97%
Rivers	Port-Harcourt	30,227	30,816	67%	64%	92%	89%	105%	101%
Rivers	Tai	6,580	6,708	100%	93%	119%	111%	144%	111%
Sokoto	Binji	7,090	7,285	70%	60%	70%	60%	59%	56%
Sokoto	Bodinga	11,841	12,167	99%	93%	94%	82%	62%	57%
Sokoto	Dange-Shuni	13,133	13,495	80%	71%	83%	74%	69%	62%
Sokoto	Gada	16,759	17,222	74%	67%	80%	76%	79%	74%
Sokoto	Goronyo	12,306	12,645	64%	59%	77%	70%	99%	83%
Sokoto	Gudu	6,450	6,628	79%	71%	87%	72%	67%	58%
Sokoto	Gwadabawa	15,618	16,049	65%	60%	76%	66%	79%	72%
Sokoto	Illela	10,159	10,439	107%	94%	120%	98%	99%	89%
Sokoto	Isa	9,863	10,135	86%	80%	90%	82%	65%	55%
Sokoto	Kebbe	8,415	8,647	66%	59%	76%	64%	81%	68%
Sokoto	Kware	9,039	9,288	115%	97%	111%	89%	95%	84%
Sokoto	Rabah	10,069	10,347	96%	87%	104%	93%	143%	110%
Sokoto	Sabon Birni	14,014	14,401	102%	92%	94%	85%	83%	70%
Sokoto	Shagari	10,559	10,850	94%	83%	74%	62%	59%	57%
Sokoto	Silame	7,046	7,240	79%	70%	77%	54%	65%	55%
Sokoto	Sokoto North	15,718	16,152	99%	72%	72%	75%	53%	49%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Sokoto	Sokoto South	13,158	13,521	74%	68%	100%	85%	73%	67%
Sokoto	Tambuwal	15,184	15,603	83%	74%	82%	70%	50%	46%
Sokoto	Tangaza	7,686	7,898	104%	98%	99%	97%	88%	81%
Sokoto	Tureta	4,615	4,743	112%	98%	131%	101%	114%	104%
Sokoto	Wamakko	12,125	12,460	87%	80%	80%	76%	75%	66%
Sokoto	Wurno	10,956	11,259	96%	89%	81%	71%	66%	56%
Sokoto	Yabo	7,764	7,978	99%	89%	101%	91%	73%	69%
Taraba	Ardo-Kola	5,367	5,509	96%	83%	134%	127%	136%	129%
Taraba	Bali	12,901	13,243	120%	107%	155%	140%	143%	128%
Taraba	Donga	8,281	8,500	100%	89%	141%	133%	137%	127%
Taraba	Gashaka	5,420	5,564	93%	73%	111%	113%	136%	134%
Taraba	Gassol	15,112	15,513	108%	99%	146%	134%	143%	138%
Taraba	Ibi	5,190	5,327	121%	110%	177%	171%	227%	222%
Taraba	Jalingo	8,635	8,864	115%	101%	144%	136%	114%	112%
Taraba	Karim Lamido	12,092	12,413	101%	87%	125%	113%	165%	151%
Taraba	Kurmi	5,652	5,801	86%	74%	121%	104%	99%	91%
Taraba	Lau	5,964	6,122	95%	88%	160%	149%	167%	155%
Taraba	Sardauna	13,858	14,225	109%	92%	133%	116%	118%	108%
Taraba	Takum	8,357	8,579	85%	80%	132%	124%	120%	110%
Taraba	Ussa	5,682	5,832	87%	78%	119%	116%	129%	121%
Taraba	Wukari	14,914	15,310	64%	60%	111%	100%	98%	95%
Taraba	Yorro	5,521	5,667	108%	101%	137%	127%	132%	121%
Taraba	Zing	7,864	8,072	86%	78%	118%	108%	122%	111%
Yobe	Bade	8,543	8,740	101%	91%	139%	110%	128%	120%
Yobe	Bursari	6,669	6,823	104%	97%	119%	116%	132%	136%
Yobe	Damaturu	5,379	5,503	155%	140%	179%	161%	189%	170%
Yobe	Fika	8,367	8,560	128%	131%	167%	165%	189%	176%
Yobe	Fune	18,382	18,806	76%	69%	127%	110%	139%	132%
Yobe	Geidam	9,613	9,835	108%	100%	139%	129%	154%	143%

State	LGA	Surv_pop_ 2023	Surv_pop_ 2024	2022_ OPV1	2022_ OPV3	2023_ OPV1	2023_ OPV3	2024_ OPV1	2024_ OPV3
Yobe	Gujba	7,951	8,134	84%	83%	105%	99%	119%	112%
Yobe	Gulani	6,326	6,472	105%	99%	173%	159%	177%	165%
Yobe	Jakusko	14,001	14,324	99%	96%	122%	120%	117%	114%
Yobe	Karasuwa	6,539	6,690	108%	106%	135%	130%	139%	133%
Yobe	Machina	3,765	3,852	123%	117%	144%	135%	150%	134%
Yobe	Nangere	5,368	5,491	104%	95%	140%	128%	155%	141%
Yobe	Nguru	9,206	9,419	89%	85%	110%	101%	143%	138%
Yobe	Potiskum	12,583	12,873	164%	156%	208%	197%	202%	195%
Yobe	Tarmuwa	4,718	4,827	100%	102%	136%	131%	165%	156%
Yobe	Yunusari	7,690	7,867	70%	60%	96%	86%	139%	125%
Yobe	Yusufari	6,789	6,946	99%	103%	125%	123%	135%	131%
Zamfara	Anka	9,973	10,280	99%	95%	105%	97%	86%	77%
Zamfara	Bakura	13,101	13,505	57%	56%	92%	88%	70%	67%
Zamfara	Birnin Magaji/Kiyaw	12,520	12,906	117%	108%	99%	90%	85%	76%
Zamfara	Bukkuyum	14,835	15,291	102%	95%	102%	94%	79%	74%
Zamfara	Bungudu	18,079	18,636	106%	97%	131%	119%	107%	99%
Zamfara	Gummi	14,337	14,779	89%	79%	139%	120%	114%	106%
Zamfara	Gusau	26,858	27,685	73%	64%	112%	100%	105%	90%
Zamfara	Kaura Namoda	19,723	20,330	77%	67%	130%	105%	93%	79%
Zamfara	Maradun	14,780	15,235	73%	67%	93%	86%	89%	81%
Zamfara	Maru	20,461	21,091	92%	81%	105%	89%	89%	77%
Zamfara	Shinkafi	9,508	9,801	87%	83%	102%	97%	88%	80%
Zamfara	Talata Mafara	15,083	15,548	70%	69%	106%	104%	83%	79%
Zamfara	Tsafe	18,646	19,220	95%	80%	106%	88%	97%	79%
Zamfara	Zurmi	20,597	21,231	79%	73%	94%	84%	90%	81%

Annex 5- Nigeria Immunisation Schedule