A Hybrid Bayesian Translational Epidemiology Framework for Precision Mop-Up Following Integrated Maternal, Newborn and Child Health Week in Kogi State, Nigeria

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ABSTRACT

Integrated Maternal, Newborn and Child Health Week (MNCHW) campaigns improve access to essential maternal, newborn and child health interventions; however, residual populations remain unreached, particularly in geographically, socioeconomically, and health-system constrained settings. Conventional post-campaign analyses predominantly describe coverage and provide limited capacity to identify who remains unreached, explain the mechanisms generating residual gaps, or spatially prioritize precision mop-up interventions.

The objective of the study to develop and apply a Hybrid Bayesian Translational Epidemiology Framework provided the milieu for the integration of evidence synthesis, Bayesian machine learning, multilevel causal mediation, and Bayesian spatial epidemiology to identify, explain, predict, and spatially prioritize residual MNCHW service gaps in Kogi State, Nigeria.

A sequential multi-phase hybrid translational epidemiology and implementation science design was applied to linked routine MNCHW, immunization, RMNCH, health-facility, contextual and geospatial datasets covering 21 Local Government Areas, 239 political wards and n=990 health facilities. PRISMA-ScR evidence synthesis informed selection of epidemiological, socioeconomic, environmental, accessibility and health-system predictors. Data management, descriptive epidemiology, Bayesian machine learning, causal mediation and statistical modeling were performed in R version 4.3.2. Bayesian Additive Regression Trees (BART) were used to estimate individual- and facility-level probabilities of residual underperformance, with Shapley Additive Explanations (SHAP) used to quantify predictor contributions; predictive performance was assessed using repeated cross-validation, discrimination, calibration and prediction-error measures. Multilevel Bayesian causal mediation analysis estimated direct, indirect and total intervention effects through community mobilization, CBHW activities, caregiver participation, outreach implementation, commodity availability, cold-chain functionality, geographic accessibility and health workforce capacity. Bayesian spatial analysis employed the Besag–York–Mollié 2 (BYM2) model implemented through R-INLA version 23.12, with queen-contiguity spatial structures, to estimate posterior relative risks, spatial dependence, exceedance probabilities and uncertainty. QGIS version 3.34 and ArcGIS Pro version 3.2 were used for spatial visualization, hotspot characterization and operational cartographic mapping. Outputs from BART, causal mediation and BYM2 were integrated into a composite Mop-up Priority Index incorporating predicted risk, spatial risk, service gaps, accessibility and facility readiness to guide precision microplanning and targeted mop-up.

The hybrid framework demonstrated strong predictive performance, with a mean 10-fold AUROC of 0.968, mean classification accuracy of 96.6%, validated AUROC of 0.961, validated RMSE of 0.033, and Bayesian R^2 of 0.83. Posterior coefficients indicated that Health Equity Index (β=0.73, 95% CrI: 0.58–0.87) and flood vulnerability (β=0.42, 0.26–0.57) increased residual service-gap risk, whereas cold-chain uptime (β=−0.68, −0.82 to −0.53), outreach frequency (β=−0.54, −0.66 to −0.41), facility readiness (β=−0.46, −0.60 to −0.32), and HRH density (β=−0.39, −0.52 to −0.25) were protective, with posterior probabilities >0.99. Multilevel mediation demonstrated important indirect implementation effects through outreach (β=0.46; approximately 44.6% mediated), cold-chain uptime (β=0.31; 42.5%), caregiver participation (β=0.41; 41.6%), commodity availability (β=0.27; 37.2%), geographic accessibility (β=0.29; 35.5%), and session implementation (β=0.24; 34.7%). The integrated pathway showed a total effect of 1.25 (95% CrI: 1.09–1.41; posterior probability >0.999).

BYM2 analysis demonstrated predominantly structured spatial variation (φ=0.62) and strong geographic dependence (spatial correlation=0.71; 95% CrI: 0.63–0.79). Posterior relative risk was highest in Ankpa (RR=2.34; 95% CrI: 1.89–2.81), Dekina (2.08; 1.71–2.49), Bassa (1.96; 1.60–2.36), and Igalamela-Odolu (1.84; 1.51–2.22), identifying these LGAs as major residual zero-dose hotspots.

Bayesian policy simulation predicted improvement in programme coverage from 69.4% (95% CrI: 65.2–73.5) under the status quo to 82.6% with improved cold-chain systems, 84.8% with combined outreach and HRH strengthening, 93.7% with an integrated intervention package, and 95.2% when the integrated package was combined with Health Equity Index targeting. The posterior probability of achieving at least 90% coverage increased from 0.42 under the status quo to 0.998 under the integrated HEI-targeted strategy.

Residual MNCHW gaps were heterogeneous, spatially structured, and strongly associated with contextual, environmental, accessibility, and health-system determinants. The findings demonstrate that software-enabled integration of R-based Bayesian machine learning, SHAP explainability, multilevel causal mediation, INLA-BYM2 spatial modeling, and QGIS/ArcGIS geospatial translation can convert routine programme data into actionable implementation intelligence. The Hybrid Bayesian Translational Epidemiology Framework therefore provides a reproducible pathway from evidence synthesis → prediction → causal explanation → spatial prioritization → precision mop-up, with potential to strengthen health equity, primary healthcare performance, resource allocation, and progress toward Universal Health Coverage.

Keywords: Integrated Maternal, Newborn and Child Health Week; Translational Epidemiology; Precision Public Health; PRISMA-ScR; Bayesian Additive Regression Trees; Multilevel Causal Mediation; BYM2; INLA; Bayesian Spatial Epidemiology; QGIS; ArcGIS Pro; Mop-up Strategy; Health Equity; Spatial Mapping; Universal Health Coverage; Implementation Science; Nigeria.

INTRODUCTION

Background to the Study

Integrated Maternal, Newborn and Child Health Week (MNCHW) is a high-impact public health strategy designed to improve equitable access to essential maternal, newborn, and child health interventions through integrated service delivery. Across low- and middle-income countries (LMICs), particularly in sub-Saharan Africa, MNCHW has become an important platform for delivering immunization, Vitamin A supplementation, deworming, growth monitoring, nutritional assessment, antenatal care (ANC), postnatal care (PNC), health education, family planning counseling, and referral services to vulnerable populations. The integrated approach minimizes missed opportunities for service delivery, optimizes limited health resources, and accelerates progress toward Sustainable Development Goal (SDG) 3 on ensuring healthy lives and promoting well-being for all at all ages.

Despite remarkable improvements in MNCHW coverage, substantial disparities remain in the uptake of essential interventions among children aged 0–59 months, pregnant women, and breastfeeding mothers. Geographic inequities, socioeconomic deprivation, weak health systems, inadequate community mobilization, workforce shortages, poor transportation infrastructure, insecurity, vaccine stock-outs, and limited accessibility to primary health care facilities continue to contribute to pockets of underserved populations. Consequently, many eligible beneficiaries are missed during campaign implementation, necessitating targeted mop-up activities to reach residual populations.

Conventional post-MNCHW monitoring and evaluation primarily rely on descriptive coverage statistics, administrative reports, and routine health information systems. These approaches rarely identify the causal mechanisms responsible for missed populations, predict individuals at greatest risk of exclusion, or characterize the spatial heterogeneity underlying residual service gaps; they only quantify service uptake. Operational managers work with only quantified service uptake data so often lack sufficient evidence to prioritize limited resources for precision mop-up interventions. The transition from descriptive monitoring to predictive, causal, and spatially informed decision-making therefore represents a critical challenge in contemporary implementation science.

Recent advances in translational epidemiology and precision public health provide innovative opportunities to address this challenge. Translational epidemiology emphasizes the systematic conversion of epidemiological evidence into actionable health policies and operational decisions. Precision public health extends this concept by integrating epidemiological, demographic, environmental, geospatial, and health systems information to target interventions to populations most in need. Together, these paradigms promote evidence-informed implementation strategies that maximize efficiency, equity, and health impact.

Machine learning techniques, particularly Bayesian Additive Regression Trees (BART), have emerged as powerful predictive tools capable of modeling complex nonlinear relationships and high-order interactions without requiring restrictive parametric assumptions. Unlike conventional regression approaches, BART estimates individualized probabilities of health outcomes while quantifying uncertainty through Bayesian inference. In the context of Integrated MNCHW, BART offers substantial potential for identifying children, pregnant women, breastfeeding mothers, and health facilities with the highest probability of being missed during campaign implementation.

Although predictive modeling identifies high-risk populations, understanding *why* interventions succeed or fail requires causal inference. Multilevel causal mediation analysis provides a rigorous framework for decomposing intervention effects into direct and indirect pathways operating through intermediate implementation mechanisms such as community mobilization, Community Based Health Workers (CBHWs), cold-chain functionality, commodity availability, outreach services, supportive supervision, and health workforce capacity. Through the quantification of these mechanisms across hierarchical structures (individuals, households, facilities, wards, and Local Government Areas), multilevel mediation analysis generates valuable evidence for optimizing implementation strategies.

Public health interventions also exhibit strong spatial dependence, whereby neighboring communities often experience similar service coverage patterns due to shared environmental, socioeconomic, and health system characteristics. Bayesian spatial epidemiology addresses this phenomenon by explicitly modeling geographic correlation. Among available spatial models, the Besag–York–Mollié 2 (BYM2) model has become the preferred Bayesian hierarchical framework because it simultaneously captures structured spatial effects and unstructured random variation while improving parameter identifiability and interpretability. BYM2 facilitates the production of posterior relative risk maps, exceedance probability surfaces, hotspot analyses, and uncertainty maps that support geographically targeted interventions.

The integration of evidence synthesis, predictive analytics, causal inference, and Bayesian spatial epidemiology within a unified implementation science framework remains uncommon in maternal and child health research, particularly in low-resource settings. Most previous studies have examined these analytical approaches independently rather than combining them into a comprehensive translational framework capable of informing operational decision-making following Integrated MNCHW campaigns.

This study therefore proposes a novel hybrid translational epidemiology framework integrating the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR), Bayesian Additive Regression Trees, multilevel causal mediation analysis, and BYM2 Bayesian spatial mapping to identify residual service gaps among children aged 0–59 months, pregnant women, breastfeeding women, and health facilities requiring mop-up interventions after Integrated MNCHW implementation in Kogi State, Nigeria. The framework seeks not only to explain coverage patterns but also to predict vulnerable populations, quantify implementation pathways, characterize spatial inequities, and translate these findings into precision microplanning for targeted outreach activities. By bridging the gap between epidemiological evidence and implementation practice, the study contributes to the advancement of precision public health, implementation science, and Universal Health Coverage.

Integrated MNCHW has substantially expanded access to life-saving maternal and child health interventions across Nigeria. Nevertheless, routine implementation continues to leave significant numbers of eligible children, pregnant women, and breastfeeding mothers unreached, particularly in geographically remote, socioeconomically disadvantaged, and health system-constrained communities. Administrative reports frequently indicate satisfactory overall coverage while masking important subnational disparities that perpetuate preventable morbidity and mortality.

Current post-campaign monitoring systems rely predominantly on descriptive analyses and administrative coverage estimates that provide limited insight into the determinants of missed populations or the mechanisms responsible for implementation failures. Consequently, mop-up activities are often conducted using generalized operational approaches rather than evidence-driven prioritization, resulting in inefficient resource allocation and persistent inequities in service delivery.

Furthermore, conventional statistical analyses inadequately address nonlinear relationships, multilevel implementation pathways, and spatial dependence inherent in public health interventions. Existing studies rarely integrate evidence synthesis, Bayesian machine learning, causal mediation analysis, and Bayesian spatial epidemiology into a single translational framework capable of informing precision mop-up planning. This methodological gap limits the ability of health managers to identify high-risk populations, understand implementation mechanisms, and geographically prioritize interventions.

Addressing these challenges requires a comprehensive analytical framework that translates routine health data into operational intelligence. The framework supports targeted mop-up strategies, improve equitable service delivery, optimize resource utilization, and strengthen progress toward Universal Health Coverage. This study seeks to fill this critical gap by developing and applying an integrated translational epidemiology framework for post-MNCHW precision public health decision-making.

Justification

The aim of this study is to develop and apply a hybrid translational epidemiology framework integrating PRISMA-ScR, Bayesian Additive Regression Trees, multilevel causal mediation analysis, and BYM2 Bayesian spatial epidemiology to identify children aged 0–59 months, pregnant women, breastfeeding women, and health facilities requiring precision mop-up interventions following Integrated Maternal, Newborn and Child Health Week implementation in Kogi State, Nigeria.

General Objective

The general objective of the study; to develop and apply a hybrid translational epidemiology framework integrates PRISMA Extension for Scoping Reviews (PRISMA-ScR), Bayesian Additive Regression Trees (BART), multilevel causal mediation analysis, and Besag–York–Mollié 2 (BYM2) Bayesian spatial mapping; identified children aged 0–59 months, pregnant women, breastfeeding women, and health facilities requiring targeted mop-up following Integrated MNCHW implementation in Kogi State, Nigeria.

Specific Objectives

The specific objectives of the study are to:

i. Conduct a PRISMA-ScR to synthesize evidence on determinants of missed MNCHW beneficiaries, implementation barriers, and effective mop-up strategies.

ii. Determine the epidemiological, socioeconomic, environmental, and health system factors associated with missed children, pregnant women, breastfeeding women, and health facilities.

iii. Develop Bayesian Additive Regression Tree models to predict individuals and facilities requiring post-MNCHW mop-up interventions.

iv. Quantify direct and indirect implementation pathways using multilevel causal mediation analysis.

v. Estimate posterior spatial risks of residual service gaps using BYM2 Bayesian hierarchical spatial models.

vi. Produce hotspot, exceedance probability, uncertainty, and posterior relative risk maps for children, pregnant women, breastfeeding women, and health facilities.

vii. Develop a composite Mop-up Priority Index integrating predictive probabilities, spatial risks, service coverage gaps, accessibility, and facility readiness.

viii. Translate epidemiological findings into evidence-based operational microplans for precision public health decision-making.

Research Questions

1. What evidence exists regarding determinants of missed MNCHW beneficiaries and successful mop-up interventions?

2. Which demographic, socioeconomic, environmental, and health system factors predict missed beneficiaries following Integrated MNCHW?

3. How accurately can Bayesian Additive Regression Trees identify populations and facilities requiring mop-up?

4. Through which implementation pathways does Integrated MNCHW influence service coverage?

5. What spatial patterns characterize residual service gaps following Integrated MNCHW?

6. Which wards and health facilities should be prioritized for precision mop-up interventions?

7. How can predictive modeling, causal inference, and Bayesian spatial epidemiology be integrated into operational decision support?

Research Hypotheses

H_{01}: There is no significant association between epidemiological, socioeconomic, environmental, and health system characteristics and the probability of being missed during Integrated MNCHW.

H_{02}: Bayesian Additive Regression Tree models do not significantly improve prediction of populations requiring mop-up compared with conventional regression models.

H_{03}: Community mobilization, CBHWs performance, health workforce availability, outreach implementation, cold-chain functionality, and commodity availability do not significantly mediate the effect of Integrated MNCHW on service coverage.

H_{04}: There is no significant spatial clustering of residual MNCHW service gaps among children aged 0–59 months, pregnant women, breastfeeding women, or health facilities.

H_{05}: The integrated PRISMA-ScR–BART–Multilevel Mediation–BYM2 framework does not significantly improve operational prioritization for mop-up interventions.

Significance of the Study

This study provides methodological innovation by integrating evidence synthesis, Bayesian machine learning, causal mediation, and spatial epidemiology into a unified translational implementation science framework. It offers policymakers and programme managers a precision public health approach for targeting post-MNCHW mop-up activities, optimizing resource allocation, improving health equity, strengthening primary health care performance, and accelerating progress toward Universal Health Coverage. The framework also contributes to the scientific literature by demonstrating how advanced epidemiological methods can be translated into routine operational decision-making in resource-constrained settings.

Scope of the Study

The study focuses on Integrated MNCHW implementation in Kogi State, Nigeria. It includes children aged 0–59 months, pregnant women, breastfeeding women, and participating health facilities. Data sources comprise MNCHW administrative datasets, DHIS2, RMNCH registers, ward microplans, health facility assessments, and geospatial datasets. Analyses encompass PRISMA-ScR, Bayesian Additive Regression Trees, multilevel causal mediation analysis, BYM2 Bayesian spatial modeling, and development of a Mop-up Priority Index for precision operational planning.

Conceptual Framework

The study is underpinned by a translational implementation framework in which evidence synthesis (PRISMA-ScR) informs predictor selection; Bayesian Additive Regression Trees estimate individual and facility-level risk; multilevel causal mediation explains implementation mechanisms; and BYM2 Bayesian spatial models identify geographic hotspots. These outputs are integrated into a Mop-up Priority Index that supports targeted microplanning, equitable resource allocation, and precision public health interventions following Integrated MNCHW. This framework links epidemiological evidence directly to implementation decisions, strengthening health system responsiveness and advancing Universal Health Coverage.

Operational Definition of Terms

The following operational definitions are aligned with the proposed study titled:

Integrated Maternal, Newborn and Child Health Week (MNCHW)

Integrated Maternal, Newborn and Child Health Week refers to a periodic, high-impact public health strategy that delivers a package of preventive and promotive health interventions to children aged 0–59 months, pregnant women, and breastfeeding mothers through fixed, outreach, and mobile service delivery platforms. These interventions include immunization, Vitamin A supplementation, deworming, nutritional screening, antenatal and postnatal care, health education, and referral services.

Translational Epidemiology

Translational epidemiology is the systematic application of epidemiological evidence, advanced analytical methods, and implementation science to convert research findings into practical public health policies, interventions, and operational decisions that improve population health outcomes.

Precision Public Health

Precision public health is an evidence-driven approach that integrates epidemiological, demographic, environmental, spatial, and health systems data to identify populations at greatest risk and deliver targeted interventions to the right people, at the right place, and at the right time.

PRISMA Extension for Scoping Reviews (PRISMA-ScR)

PRISMA-ScR is an internationally recognized reporting guideline that provides a structured framework for conducting and reporting scoping reviews to systematically identify, map, and synthesize existing evidence, knowledge gaps, implementation barriers, and research priorities relevant to a public health problem.

Bayesian Additive Regression Trees (BART)

Bayesian Additive Regression Trees is a Bayesian machine learning algorithm that predicts outcomes by combining multiple regression trees to model complex nonlinear relationships and high-order interactions while providing probabilistic estimates and uncertainty measures.

Bayesian Machine Learning

Bayesian machine learning refers to statistical learning methods that combine observed data with prior probability distributions to estimate predictive models while explicitly quantifying uncertainty in predictions.

Multilevel Causal Mediation Analysis

Multilevel causal mediation analysis is a hierarchical statistical approach that decomposes the total effect of an intervention into direct and indirect pathways across nested data structures, thereby identifying mechanisms through which implementation strategies influence health outcomes.

Mediation Effect

A mediation effect is the proportion of an intervention's influence on an outcome that operates through one or more intermediate variables, such as community mobilization, cold-chain functionality, outreach services, or health worker availability.

Bayesian Spatial Epidemiology

Bayesian spatial epidemiology is the application of Bayesian statistical models to analyze the geographic distribution of diseases or health service coverage while accounting for spatial dependence, uncertainty, and contextual determinants.

BYM2 Spatial Model

The Besag–York–Mollié 2 (BYM2) model is a Bayesian hierarchical spatial model that combines structured spatial effects and unstructured random effects to estimate geographically smoothed risks while reducing

model overparameterization and improving interpretability.

Spatial Mapping

Spatial mapping is the visualization and statistical analysis of geographically referenced health data to identify spatial patterns, clusters, hotspots, cold spots, and areas requiring targeted public health interventions.

Hotspot

A hotspot is a geographic area with significantly higher-than-expected concentrations of missed beneficiaries, poor service coverage, or elevated health risks after accounting for population characteristics and spatial correlation.

Exceedance Probability

Exceedance probability is the Bayesian probability that the estimated disease risk or service gap in a geographic area exceeds a predefined threshold, thereby identifying locations requiring urgent intervention.

Posterior Relative Risk

Posterior relative risk is the Bayesian estimate of the likelihood that a geographic area experiences a higher or lower risk compared with the overall study population after incorporating observed data and prior distributions.

Mop-up Intervention

A mop-up intervention is a targeted follow-up activity conducted immediately after an Integrated MNCHW campaign to identify and provide essential health services to eligible individuals and communities who were missed during the primary implementation period.

Mop-up Priority Index (MPI)

The Mop-up Priority Index is a composite operational score developed by integrating predictive probabilities from BART, Bayesian spatial risks from the BYM2 model, service coverage gaps, accessibility indicators, and health facility readiness to prioritize locations for post-MNCHW outreach.

Health Facility Readiness

Health facility readiness is the capacity of a health facility to provide quality MNCHW services, measured through the availability of trained personnel, essential medicines, vaccines, cold-chain equipment, logistics, reporting tools, infrastructure, and supportive supervision.

Knowledge Translation

Knowledge translation is the dynamic process of synthesizing, disseminating, exchanging, and applying research evidence to improve health policies, clinical practice, public health programming, and implementation outcomes.

LITERATURE REVIEW

Introduction

Maternal, newborn, and child health (MNCH) remains a cornerstone of global public health and sustainable development because the survival and well-being of women and children directly reflect the performance, resilience, and equity of health systems. Despite remarkable improvements in healthcare delivery over the past three decades, preventable maternal, neonatal, and under-five deaths continue to account for a substantial proportion of the global disease burden, particularly in low- and middle-income countries (LMICs). According to recent global estimates, approximately 4.8 million mothers and children die annually from preventable causes, with sub-Saharan Africa bearing nearly two-thirds of this burden. These deaths are largely attributable to inadequate access to quality antenatal care, skilled birth attendance, postnatal care, immunization, nutrition services, and timely management of childhood illnesses. Consequently, improving coverage of essential maternal and child health interventions remains a global priority under Sustainable Development Goal (SDG) 3, Universal Health Coverage (UHC), the Global Immunization Agenda 2030 (IA2030), and the Primary Health Care (PHC) revitalization agenda [2–6]. The Kogi State 2026 RI health-facility microplan covered an estimated 6,040,079 total population, including approximately 260,039 surviving infants (<1 year) who constitute the principal routine immunization target population. However, only about 3,096,441 people (including 135,502 surviving infants) were linked to facilities classified as equipped, indicating a substantial readiness gap between the population requiring services and the facility capacity available to deliver them;

notably, n=286 equipped facilities also had buildings suitable for SDD installation, accounting for approximately 3.09 million people and 135,144 surviving infants. These findings indicate that facility readiness, infrastructure, and access constraints are critical determinants of effective RI service delivery and equitable coverage in Kogi State, with important implications for UHC, Immunization Agenda 2030 and SDG 3.2/3.8 implementation.

Integrated Maternal, Newborn and Child Health Week (MNCHW) has emerged as one of the most widely adopted implementation strategies for delivering multiple life-saving interventions simultaneously to children aged 0–59 months, pregnant women, and breastfeeding mothers. Unlike vertical health programmes that address individual diseases independently, Integrated MNCHW combines immunization, Vitamin A supplementation, deworming, nutritional screening, antenatal care, postnatal care, family planning counseling, growth monitoring, and health education within a single service delivery platform. This integrated approach promotes efficiency, minimizes missed opportunities, improves equity, and optimizes scarce human and financial resources. In Nigeria, Integrated MNCHW complements routine primary healthcare services and supports implementation of the National Health Sector Renewal Investment Initiative, the Basic Health Care Provision Fund (BHCPF), and the National Primary Health Care Development Agency's integrated service delivery strategy [7–12].

Although Integrated MNCHW has substantially increased intervention coverage, persistent inequities remain across geographic regions, socioeconomic groups, and vulnerable populations. Administrative reports often demonstrate high aggregate coverage while concealing localized clusters of missed children, pregnant women, breastfeeding mothers, and poorly performing health facilities. These residual gaps are frequently associated with weak community engagement, inadequate microplanning, difficult terrain, poor transportation infrastructure, insecurity, population mobility, health workforce shortages, commodity stock-outs, weak cold-chain systems, and social determinants of health. Consequently, conventional post-campaign monitoring approaches provide limited information regarding the underlying mechanisms responsible for implementation failure or the geographic distribution of residual service gaps.

Traditional epidemiological analyses have primarily relied upon descriptive statistics and generalized linear regression models for evaluating programme performance. Although these approaches remain valuable, they possess several methodological limitations when applied to complex health systems. They generally assume linear relationships, fail to capture high-order interactions among determinants, inadequately address hierarchical population structures, and frequently ignore spatial autocorrelation. Furthermore, they rarely explain the implementation mechanisms through which interventions influence outcomes or identify the populations most likely to benefit from targeted follow-up activities. These limitations constrain evidence-based decision-making and reduce the effectiveness of post-campaign mop-up interventions.

The emergence of translational epidemiology has fundamentally transformed the relationship between epidemiological research and implementation practice. Translational epidemiology emphasizes moving beyond describing disease patterns to generating actionable evidence that directly informs policy formulation, programme implementation, and operational decision-making. This paradigm aligns closely with precision public health, which integrates epidemiological, demographic, environmental, socioeconomic, behavioural, geospatial, and health systems information to identify populations at greatest risk and allocate interventions with greater precision. Together, these complementary disciplines seek to ensure that health interventions reach the right populations, in the right locations, at the right time, while maximizing efficiency, effectiveness, and equity [9–15].

Recent developments in Bayesian statistics and artificial intelligence have further expanded the methodological capacity of epidemiological research. Bayesian Additive Regression Trees (BART) represent one of the most powerful machine learning algorithms for public health prediction because they accommodate nonlinear relationships, automatically detect complex interactions, estimate individualized risks, and quantify predictive uncertainty through Bayesian inference. Unlike conventional regression approaches, BART requires minimal assumptions regarding model specification and has demonstrated superior predictive performance across diverse clinical and population health applications. In the context of Integrated MNCHW, BART provides an opportunity to identify children, pregnant women, breastfeeding mothers, and health facilities most likely to remain unreached following campaign implementation [45–50].

Prediction alone, however, is insufficient for implementation improvement. Understanding the causal mechanisms underlying intervention effectiveness requires analytical methods capable of distinguishing direct programme effects from intermediate implementation pathways. Multilevel causal mediation analysis has therefore emerged as an important extension of causal inference in implementation science. Through the partitioning total intervention effects into direct and indirect components operating through mediating variables such as community mobilization, Community Based Health Workers (CBHWs), cold-chain functionality, outreach implementation, supportive supervision, health workforce capacity, and commodity availability, mediation analysis enables programme managers to identify the mechanisms most responsible for implementation success or failure. When incorporated within hierarchical data structures, multilevel mediation further accounts for clustering at household, facility, ward, and Local Government Area levels.

Public health interventions are inherently spatial because population characteristics, environmental exposures, accessibility, and health service availability vary geographically. Spatial dependence implies that neighbouring communities frequently experience similar health outcomes due to shared contextual determinants. Failure to account for spatial autocorrelation may therefore bias epidemiological estimates and underestimate uncertainty. Bayesian spatial epidemiology addresses these limitations by incorporating geographic dependence directly into statistical models. Among available Bayesian disease mapping techniques, the Besag–York–Mollié 2 (BYM2) model has become the preferred framework because it combines structured spatial effects with unstructured random variation while improving parameter identifiability and computational stability. BYM2 enables estimation of posterior relative risks, exceedance probabilities, uncertainty measures, hotspot detection, and operational priority maps that are directly applicable to precision public health planning [56–61].

An equally important component of translational implementation research is evidence synthesis. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) provides a standardized methodology for identifying, mapping, and synthesizing available evidence while highlighting knowledge gaps requiring further investigation. PRISMA-ScR was applied in this study to serve as the foundational phase for identifying determinants of missed beneficiaries, implementation barriers, successful mop-up strategies, spatial modeling approaches, and predictive algorithms reported across global literature. The resulting evidence informs selection of variables for subsequent predictive, causal, and spatial analyses, thereby strengthening methodological rigor and ensuring alignment with international reporting standards.

Although numerous studies have separately investigated Integrated MNCHW implementation, Bayesian machine learning, mediation analysis, or spatial epidemiology, relatively few have integrated these complementary methodologies within a unified translational framework. Existing literature often focuses on programme coverage, determinants of health service utilization, or spatial inequalities without explicitly linking evidence synthesis, predictive analytics, causal inference, and Bayesian disease mapping to operational decision-making. Consequently, important opportunities remain to develop comprehensive analytical frameworks capable of translating routine health information into actionable implementation intelligence.

The critical review of contemporary literature is relevant to the proposed study. It examines conceptual perspectives on Integrated MNCHW, translational epidemiology, implementation science, precision public health, Bayesian machine learning, multilevel causal inference, and Bayesian spatial epidemiology. It further evaluates theoretical frameworks underpinning implementation research, synthesizes empirical evidence from global, regional, and Nigerian contexts, identifies methodological strengths and limitations of previous studies, and establishes the scientific rationale for integrating PRISMA-ScR, Bayesian Additive Regression Trees, multilevel causal mediation analysis, and BYM2 spatial mapping within a unified translational epidemiology framework for precision mop-up following Integrated MNCHW implementation in Kogi State, Nigeria.

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Concept of Integrated Maternal, Newborn and Child Health Week (MNCHW)

Integrated Maternal, Newborn and Child Health Week (MNCHW) is an evidence-based implementation strategy designed to accelerate the delivery of high-impact maternal, newborn, and child health interventions through synchronized, time-limited campaigns integrated within routine primary healthcare systems [22, 46, 47, 48, 51]. The concept emerged from recognition that many maternal and child health interventions share common target populations, delivery platforms, logistics systems, and community engagement structures. Rather than implementing these interventions independently through fragmented vertical programmes, Integrated MNCHW consolidates them into coordinated service delivery events that improve efficiency, expand coverage, reduce operational costs, and strengthen health system performance [46, 47, 68, 69].

Historically, child survival initiatives focused on disease-specific interventions such as immunization campaigns, Vitamin A supplementation programmes, oral polio vaccination, or nutritional interventions. While these vertical approaches achieved substantial disease-specific successes, they often duplicated resources, overburdened frontline health workers, and failed to address the interconnected determinants of maternal and child health. The evolution toward integrated service delivery was driven by global initiatives including the Integrated Management of Childhood Illness (IMCI), the Every Woman Every Child movement, the Global Strategy for Women's, Children's and Adolescents' Health, and the Astana Declaration on Primary Health Care. These initiatives emphasized person-centred, equitable, and comprehensive healthcare delivery across the life course [46, 48, 51, 54, 76].

Integrated MNCHW generally targets three principal beneficiary groups: children aged 0–59 months, pregnant women, and breastfeeding mothers. Interventions for children commonly include routine immunization, catch-up vaccination, Vitamin A supplementation, deworming, growth monitoring, nutritional assessment, screening for acute malnutrition, and caregiver counseling on infant and young child feeding. Pregnant women receive antenatal care, tetanus-containing vaccination where indicated, intermittent preventive treatment for malaria, iron and folic acid supplementation, nutrition counseling, birth preparedness education, and referral for obstetric complications. Breastfeeding mothers benefit from postnatal care, family planning counseling, exclusive breastfeeding support, maternal nutrition services, newborn care education, and linkage to routine primary healthcare services [22, 35, 37, 54, 64, 75, 90].

Operationally, Integrated MNCHW employs multiple delivery strategies, including fixed health facility sessions, temporary outreach posts, mobile teams serving hard-to-reach communities, community distribution platforms, and house-to-house mobilization by community volunteers and CBHWs. These complementary approaches enhance geographical accessibility while improving demand generation through community engagement, religious leaders, traditional institutions, women's groups, schools, and local media. Effective implementation requires robust microplanning, commodity forecasting, logistics management, workforce deployment, supportive supervision, real-time monitoring, and post-implementation mop-up activities targeting populations missed during the primary campaign [22, 27, 51, 60, 67, 81, 84, 87].

In Nigeria, the Integrated MNCHW represents an integral component of the national Primary Health Care revitalization strategy and contributes to achieving the objectives of the National Health Sector Strategic Development Plan, the Basic Health Care Provision Fund, the National Strategic Health Development Plan II, the National Immunization Policy, and Immunization Agenda 2030 [9, 22, 23, 51, 92, 94]. At the subnational level, implementation is coordinated through State Primary Health Care Development Agencies in collaboration with Local Government Health Authorities, development partners, civil society organizations, and community structures. This decentralized governance model facilitates adaptation of implementation strategies to local epidemiological, demographic, cultural, and geographical contexts while promoting ownership and sustainability [7, 68, 69, 92, 96].

From an implementation science perspective, Integrated MNCHW is more than a campaign; it is a complex adaptive intervention operating within dynamic health systems. Its effectiveness depends not only on intervention efficacy but also on contextual factors such as governance, financing, workforce capacity, health information systems, commodity security, community participation, and intersectoral collaboration [4, 7, 8, 24, 68, 72, 104, 106]. Consequently, evaluating Integrated MNCHW requires analytical approaches capable of capturing multilevel interactions, implementation mechanisms, spatial heterogeneity, and contextual influences. These considerations provide the rationale for adopting the hybrid translational epidemiology framework proposed in this study, which integrates evidence synthesis, Bayesian machine learning, causal mediation analysis, and Bayesian spatial modeling to support precision mop-up and equitable health service delivery [5, 6, 17, 18, 28, 30, 42, 87].

Concept of Translational Epidemiology

Translational epidemiology is an emerging discipline that bridges the gap between epidemiological research and public health practice by transforming scientific evidence into policies, programmes, and interventions that improve population health outcomes [17, 42, 70]. Unlike traditional epidemiology, which primarily focuses on identifying disease determinants, measuring disease frequency, and evaluating risk factors, translational epidemiology extends the epidemiological continuum to include the application, implementation, dissemination, and evaluation of evidence-based interventions within real-world health systems. It integrates classical epidemiological principles with implementation science, health policy, systems thinking, precision public health, data science, and decision analytics to ensure that research findings lead to measurable improvements in healthcare delivery and population health [4, 17, 24, 68, 70, 111, 112].

The concept evolved from the broader translational science movement that emerged in the early twenty-first century in response to growing concerns regarding the prolonged interval between scientific discovery and routine clinical or public health implementation. Although biomedical research has generated substantial advances in diagnostics, therapeutics, vaccines, and preventive interventions, numerous evidence-based innovations require many years before widespread adoption in health systems. This "know-do gap" represents a major obstacle to improving health outcomes, particularly in low- and middle-income countries (LMICs), where resource limitations, weak health systems, and contextual barriers frequently delay implementation. Translational epidemiology addresses this challenge by systematically integrating epidemiological evidence into planning, implementation, monitoring, evaluation, and policy formulation [4, 8, 17, 24, 70, 103].

The translational epidemiology continuum is commonly described using successive stages of evidence translation. The **T0** stage involves basic scientific discovery and identification of biological, behavioural, environmental, and social determinants of health. **T1** translation converts these discoveries into clinical or public health interventions through efficacy studies and early implementation research. **T2** translation evaluates intervention effectiveness and develops evidence-based guidelines for programme implementation. **T3** translation focuses on dissemination and integration of proven interventions into routine healthcare practice through implementation science. **T4** translation, the highest level of the continuum, examines population-level effectiveness, equity, sustainability, and policy impact under real-world conditions. Contemporary implementation science has expanded this framework by incorporating continuous learning cycles, health systems strengthening, and precision public health approaches that promote adaptive implementation and ongoing quality improvement [4, 17, 24, 70, 102, 103, 104, 105].

Within maternal, newborn, and child health programmes, translational epidemiology shifts programme evaluation from descriptive reporting toward operational decision support. Rather than merely estimating intervention coverage, it seeks to answer critical implementation questions: Who remains unreached? Why were they missed? Which implementation mechanisms contributed to programme success or failure? Where are residual service gaps concentrated? Which interventions should be prioritized? Addressing these questions requires integrating epidemiological surveillance, predictive modeling, causal inference, spatial analytics, implementation science, and policy translation into a single analytical framework capable of supporting evidence-based decision-making [17, 42, 68, 70, 74, 83, 99].

Precision public health represents one of the most important applications of translational epidemiology. Precision public health extends the concept of precision medicine from individuals to populations by using epidemiological, demographic, socioeconomic, behavioural, environmental, genomic (where applicable), and geospatial data to identify vulnerable populations and deliver interventions with greater precision. Rather than applying uniform strategies across heterogeneous populations, precision public health recognizes that health risks and implementation barriers differ substantially across geographic locations and social groups. Consequently, interventions are tailored according to local epidemiological profiles, health system capacity, accessibility, and contextual determinants, thereby improving efficiency, equity, and programme effectiveness [82, 84, 87, 111, 112, 113, 114, 115].

Recent advances in artificial intelligence, machine learning, and Bayesian statistics have significantly expanded the analytical capabilities of translational epidemiology. Machine learning algorithms, particularly Bayesian Additive Regression Trees (BART), enable accurate prediction of individuals and communities at highest risk of adverse health outcomes by modeling complex nonlinear relationships and high-order interactions among numerous predictors. Unlike conventional regression models that require predefined functional relationships, BART automatically identifies influential predictors while quantifying uncertainty through Bayesian inference. These characteristics make BART especially suitable for predicting children, pregnant women, breastfeeding mothers, and health facilities requiring post-campaign mop-up following Integrated Maternal, Newborn and Child Health Week (MNCHW) implementation [5, 14, 16, 111, 113].

Prediction alone, however, does not explain the mechanisms through which interventions influence outcomes. Translational epidemiology therefore incorporates causal inference methodologies to identify implementation pathways that determine programme effectiveness. Multilevel causal mediation analysis has emerged as an important methodological advancement because it partitions the total effect of an intervention into direct effects and indirect effects operating through intermediate implementation mechanisms such as community mobilization, Community Based Health Workers (CBHWs), outreach services, cold-chain functionality, supportive supervision, health workforce capacity, and commodity availability [6, 15, 29, 40, 41]. Understanding these pathways enables programme managers to strengthen specific components of implementation rather than relying solely on overall coverage estimates [27, 70].

Another defining characteristic of translational epidemiology is its recognition of spatial heterogeneity in disease occurrence and health service utilization. Population health outcomes are influenced not only by individual characteristics but also by geographic accessibility, environmental conditions, socioeconomic context, and health system performance. Bayesian spatial epidemiology therefore plays a central role in translational research by identifying geographic hotspots, estimating spatially smoothed risks, and quantifying uncertainty across administrative units [2, 18, 21, 28, 30]. The Besag–York–Mollié 2 (BYM2) Bayesian hierarchical model has become the preferred approach for disease mapping because it simultaneously models structured spatial dependence and unstructured random variation while improving model stability and interpretability [28, 31, 32]. Within Integrated MNCHW programmes, BYM2 spatial mapping enables identification of wards, communities, and health facilities requiring targeted mop-up activities, thereby transforming epidemiological analyses into actionable implementation intelligence [21, 28, 84, 87].

Evidence synthesis constitutes another essential component of translational epidemiology. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) provides a standardized framework for identifying, mapping, and synthesizing available evidence while highlighting research gaps and implementation challenges [25]. In translational implementation research, PRISMA-ScR informs variable selection, conceptual framework development, and analytical modeling by integrating global evidence regarding intervention effectiveness, implementation barriers, determinants of service utilization, and successful programme strategies. Consequently, evidence synthesis serves as the foundation upon which predictive analytics, causal inference, and spatial epidemiology are subsequently developed [25, 70].

The application of translational epidemiology has expanded considerably across immunization programmes, infectious disease surveillance, maternal health, non-communicable diseases, nutrition, pandemic preparedness, and health systems strengthening [17, 42, 68, 70, 111, 116]. During recent global public health emergencies, including the COVID-19 pandemic, translational epidemiology facilitated rapid integration of surveillance data, predictive modeling, genomic epidemiology, spatial analysis, and implementation research to support timely policy decisions [104, 105, 116, 117, 118, 122, 123]. Similarly, immunization programmes increasingly employ translational epidemiological approaches to identify zero-dose children, predict vaccine hesitancy, optimize outreach planning, monitor equity, and evaluate implementation fidelity [37, 51, 60, 62, 66, 67, 87]. These experiences demonstrate the capacity of translational epidemiology to accelerate evidence-informed decision-making across diverse public health contexts [17, 70, 111].

Despite its growing importance, translational epidemiology faces several methodological and operational challenges. High-quality implementation depends upon the availability of reliable routine health information systems, interoperable databases, geospatial datasets, and timely surveillance information. Data incompleteness, inconsistent reporting, selection bias, and measurement error may reduce predictive accuracy and compromise causal inference. Advanced analytical methods also require substantial computational infrastructure and multidisciplinary expertise spanning epidemiology, biostatistics, computer science, implementation science, geographic information systems (GIS), and health policy [68, 70, 84, 98]. Furthermore, translating analytical findings into operational decisions requires strong institutional leadership, stakeholder engagement, and governance mechanisms capable of supporting evidence-informed planning and resource allocation [7, 24, 27, 68, 69, 104, 106].

Notwithstanding these challenges, translational epidemiology offers a comprehensive scientific framework for improving maternal and child health programmes. Its integration of evidence synthesis, machine learning, causal inference, Bayesian spatial modeling, and implementation science provides programme managers with robust decision-support tools capable of identifying residual service gaps, prioritizing interventions, and optimizing resource utilization [4, 5, 6, 18, 21, 25, 28, 30, 70]. Within the context of Integrated MNCHW, this approach facilitates precision mop-up planning by identifying children aged 0–59 months, pregnant women, breastfeeding mothers, and health facilities most likely to have been missed during campaign implementation. Consequently, translational epidemiology strengthens health equity, improves implementation effectiveness, enhances accountability, and accelerates progress toward Universal Health Coverage (UHC), Immunization Agenda 2030 (IA2030), and the Sustainable Development Goals (SDGs) [34, 46, 49, 51, 56, 61, 62, 100].

In the present study, translational epidemiology constitutes the overarching scientific paradigm that integrates PRISMA-ScR for evidence synthesis, Bayesian Additive Regression Trees for predictive modeling, multilevel causal mediation analysis for elucidating implementation pathways, and BYM2 Bayesian spatial epidemiology for geographic prioritization of mop-up activities [5, 6, 25, 28, 30]. By combining these complementary methodologies within a unified implementation science framework, the study seeks to transform routine MNCHW programme data into actionable operational intelligence, thereby advancing precision public health and strengthening evidence-based decision-making in Kogi State, Nigeria [4, 17, 68, 70, 111]. This integrated framework represents a significant methodological advancement beyond conventional programme evaluation by explicitly linking epidemiological evidence to implementation practice, health systems strengthening, and equitable service delivery [17, 24, 68, 69, 70].

Precision Public Health

Precision public health applies epidemiological, demographic, geospatial, environmental, and health systems data to deliver interventions to populations at greatest risk. Unlike conventional public health programmes that employ uniform intervention strategies, precision public health recognizes that disease burden, health service accessibility, and implementation barriers vary considerably across geographic locations and population groups. Consequently, interventions are prioritized according to local epidemiological risk, health system capacity, and contextual determinants [82, 84, 87, 111, 112, 113, 114, 115].

Within Integrated MNCHW programmes, precision public health facilitates identification of underserved children aged 0–59 months, pregnant women, breastfeeding mothers, and health facilities requiring targeted mop-up activities. Predictive analytics and spatial epidemiology enable programme managers to optimize outreach planning, improve resource allocation, reduce inequities, and strengthen primary healthcare performance [5, 18, 21, 28, 30, 62, 67, 87]. This study adopts precision public health as the operational framework for translating epidemiological evidence into geographically targeted interventions [111, 112].

Implementation Science

Implementation science investigates methods that promote the systematic adoption, integration, and sustainability of evidence-based interventions within routine health systems [8, 24]. Rather than evaluating whether an intervention works under ideal conditions, implementation science examines how interventions are delivered, why implementation succeeds or fails, and which contextual factors influence programme effectiveness [4, 7, 8, 24, 27, 106].

Integrated MNCHW represents a complex health systems intervention whose effectiveness depends upon governance, workforce capacity, logistics, community participation, supportive supervision, financing, and health information systems [7, 68, 69, 72, 73]. Consequently, implementation outcomes such as coverage, fidelity, reach, equity, acceptability, and sustainability provide important indicators for programme evaluation [12, 27, 103, 106]. This study applies implementation science principles to translate predictive and spatial evidence into operational decision-making [4, 7, 24, 70].

PRISMA Extension for Scoping Reviews (PRISMA-ScR)

PRISMA-ScR provides internationally accepted guidance for conducting and reporting scoping reviews. Unlike systematic reviews that focus primarily on intervention effectiveness, scoping reviews identify the breadth of available evidence, summarize key concepts, map implementation strategies, and identify knowledge gaps [25].

Within the present study, PRISMA-ScR serves as the evidence synthesis component that informs selection of epidemiological determinants, implementation variables, predictive factors, and contextual indicators included in subsequent Bayesian modeling. This approach strengthens methodological transparency while ensuring that predictive models are grounded in existing scientific evidence [25].

Bayesian Additive Regression Trees (BART)

Bayesian Additive Regression Trees are flexible machine learning algorithms that combine multiple regression trees within a Bayesian framework to estimate individualized outcome probabilities. BART accommodates nonlinear relationships, complex interactions, and high-dimensional predictor variables without requiring restrictive model assumptions [5, 14, 16].

Compared with conventional logistic regression, BART generally demonstrates superior predictive performance while providing probabilistic uncertainty estimates. In maternal and child health programmes, BART has been increasingly applied to identify vulnerable populations, predict health service utilization, and optimize intervention targeting [5, 111, 113]. In this study, BART predicts children, pregnant women, breastfeeding mothers, and health facilities requiring mop-up following Integrated MNCHW.

Multilevel Causal Mediation Analysis

Although predictive models identify high-risk populations, they do not explain the mechanisms through which interventions influence outcomes. Multilevel causal mediation analysis addresses this limitation by partitioning intervention effects into direct and indirect pathways operating through intermediate implementation factors [6, 15, 29, 40, 41].

Potential mediators include community mobilization, CBHWs household visitation, outreach implementation, cold-chain functionality, commodity availability, supportive supervision, and workforce capacity. Because individuals are nested within households, communities, health facilities, wards, and Local Government Areas, multilevel mediation appropriately accounts for hierarchical data structures while estimating contextual influences on programme performance [6, 29, 40, 41].

Bayesian Spatial Epidemiology

Health outcomes exhibit substantial spatial dependence because neighbouring communities often share similar environmental, socioeconomic, and health system characteristics. Bayesian spatial epidemiology explicitly models these geographic relationships while accounting for uncertainty and small-area variation [2, 18, 21, 28, 30].

Bayesian disease mapping has become an essential component of precision public health because it enables identification of localized health inequities that are often obscured by aggregate statistics [18, 21, 28, 84, 87]. Within Integrated MNCHW programmes, Bayesian spatial epidemiology supports evidence-based prioritization of outreach activities by identifying residual clusters of missed beneficiaries [21, 28, 87].

BYM2 Bayesian Spatial Model

The Besag–York–Mollié 2 (BYM2) model represents the current standard for Bayesian disease mapping because it combines structured spatial dependence with unstructured heterogeneity while reducing parameter identifiability problems observed in earlier models [28, 31, 32].

BYM2 generates posterior relative risk estimates, exceedance probabilities, uncertainty maps, and hotspot analyses that facilitate operational decision-making. In this study, BYM2 identifies wards and health facilities with the highest probability of residual missed populations following Integrated MNCHW implementation.

Geographic Information Systems and Spatial Mapping

Geographic Information Systems (GIS) integrate epidemiological, demographic, environmental, and health systems data to visualize geographic patterns of disease and service utilization. GIS has become indispensable for microplanning, accessibility analysis, health resource allocation, and programme monitoring [21, 84, 87].

Combining GIS with Bayesian spatial models enables production of risk maps, accessibility maps, hotspot analyses, and operational priority maps that support precision public health [18, 21, 28, 84, 87]. These tools strengthen evidence-based planning for post-MNCHW mop-up activities.

Mop-up Strategy and Precision Microplanning

Mop-up activities constitute targeted follow-up interventions designed to reach eligible beneficiaries missed during the primary implementation period. Effective mop-up depends upon accurate identification of missed populations, efficient allocation of outreach teams, and continuous monitoring of programme performance [22, 51, 60, 62, 67, 87].

Precision microplanning integrates predictive modeling, spatial epidemiology, routine health information systems, and community intelligence to prioritize high-risk settlements and optimize deployment of limited resources [21, 51, 62, 67, 87]. This study proposes a composite Mop-up Priority Index combining predictive probabilities, Bayesian spatial risks, service coverage gaps, accessibility, and health facility readiness [5, 21, 28, 87].

Universal Health Coverage and Health Equity

Universal Health Coverage (UHC) requires equitable access to quality health services without financial hardship. Achieving UHC depends not only on increasing overall service coverage but also on reducing disparities between population groups and geographic locations [34, 46, 49, 56, 61, 100].

Integrated MNCHW contributes directly to UHC by improving access to preventive maternal and child health services. However, persistent inequities necessitate precision implementation approaches capable of identifying underserved populations and targeting interventions accordingly [46, 49, 51, 56, 82, 100]. The hybrid analytical framework proposed in this study supports equitable resource allocation and contributes to achieving SDG 3, Immunization Agenda 2030, and the Primary Health Care revitalization agenda [34, 48, 51, 56, 61, 62, 100].

Theoretical Framework

This study is informed by six complementary theoretical perspectives:

- **Knowledge-to-Action (KTA) Framework:** Explains how scientific evidence is translated into policy and practice.
- **Consolidated Framework for Implementation Research (CFIR):** Identifies contextual determinants influencing implementation success.
- **RE-AIM Framework:** Evaluates programme Reach, Effectiveness, Adoption, Implementation, and Maintenance.
- **Socio-Ecological Model:** Recognizes that health behaviours are influenced by individual, interpersonal, community, organizational, and policy factors.
- **Andersen's Behavioural Model of Health Service Utilization:** Explains health service utilization through predisposing, enabling, and need factors.
- **Precision Public Health Framework:** Supports risk stratification and targeted intervention delivery.

2.3.1 Translational Epidemiology–Precision Public Health Hybridization Theory for Precision Mop-Up and Emergency Preparedness

Theoretical proposition

This study proposes a **Translational Epidemiology–Precision Public Health Hybridization Theory (TE-PPH Theory)** to explain how epidemiological evidence can be transformed into geographically targeted, mechanism-informed, and operationally actionable interventions for populations missed during Integrated Maternal, Newborn and Child Health Week (MNCHW). The theory extends conventional translational epidemiology and precision public health by conceptualizing mop-up not merely as a post-campaign corrective activity, but as an **adaptive population-health intervention that simultaneously closes residual service gaps, strengthens health-system readiness, and generates preparedness intelligence for subsequent public health emergencies**.

The proposed theory is grounded in the premise that health programme implementation occurs within heterogeneous populations and dynamic health systems. Consequently, aggregate programme coverage may conceal localized populations that remain unreached because of geographic isolation, socioeconomic disadvantage, insecurity, population mobility, weak community engagement, inadequate workforce, commodity interruptions, poor cold-chain functionality, or limited facility readiness. The existing study framework already recognizes this problem by integrating PRISMA-ScR, BART, multilevel causal mediation and BYM2 spatial epidemiology into a sequential pathway from evidence generation to precision mop-up. The proposed theory extends that pathway by explicitly introducing **emergency preparedness, resilience, feedback, learning and adaptive reallocation** as downstream and iterative components.

The theoretical proposition can therefore be stated as follows:

When epidemiological evidence is continuously translated into risk-stratified, spatially targeted and implementation-informed action, post-intervention mop-up becomes an adaptive preparedness function that improves immediate service coverage while simultaneously strengthening population-level resilience, health-system readiness and future emergency response capacity.

This proposition moves the framework beyond prediction alone. BART identifies who or which facilities are likely to remain unreached; multilevel causal mediation explains why implementation gaps occur; BYM2 identifies where residual risk is concentrated; and the Mop-up Priority Index determines where limited operational resources should be deployed first. The resulting intervention generates new surveillance and implementation information, which is fed back into the health system for subsequent planning. This makes the framework **iterative rather than purely linear**.

The Hybridization concept

The term **hybridization** refers to the deliberate integration of two traditionally complementary but operationally distinct paradigms. **Translational epidemiology** provides the evidence-to-action pathway. It converts epidemiological observations into predictive, causal and policy-relevant evidence. **Precision public health**, in contrast, provides the targeting logic through which interventions are differentiated according to risk, geography, population vulnerability and health-system capacity.

The hybrid therefore operates through four linked questions:

1. **Who is most likely to be missed?** — predictive epidemiology;
2. **Why are they being missed?** — causal and implementation epidemiology;
3. **Where is residual risk concentrated?** — Bayesian spatial epidemiology;
4. **What should be done, where, when and with what resources?** — precision implementation and operational decision support.

The original study framework establishes these analytical relationships by combining evidence synthesis, predictive modeling, causal inference and spatial epidemiology. The Hybridization theory adds a fifth dimension: **preparedness learning**, whereby information generated during mop-up becomes an input into future emergency preparedness and PHC resilience.

Thus: **Evidence → Prediction → Explanation → Spatial prioritisation → Action → Monitoring → Learning → Preparedness → Improved response capacity.**

The five-domain architecture of the TE-PPH Theory

The proposed theory consists of five interconnected domains.

Domain I: Epidemiological intelligence

The first domain establishes the population-health evidence base. Routine MNCHW data, demographic characteristics, socioeconomic variables, environmental information, health-system indicators, facility characteristics, community information and geospatial data are integrated with evidence identified through PRISMA-ScR.

This domain answers the question:

What is the epidemiological distribution of unmet need?

Rather than treating coverage as a single aggregate outcome, the framework conceptualizes unmet need as a multidimensional phenomenon involving **individual susceptibility, household characteristics, community context, facility readiness and geographic accessibility**.

Domain II: Predictive and causal intelligence

The second domain combines **BART predictive modeling** with **multilevel causal mediation analysis**.

BART estimates the probability that an eligible beneficiary or health facility will remain unreached. Its principal contribution is therefore **risk prediction**. BART is particularly useful where nonlinear relationships and interactions among determinants are expected.

Causal mediation contributes a different form of intelligence. It investigates the pathways through which implementation factors influence service coverage. Potential pathways include community mobilization, community health worker performance, outreach frequency, workforce availability, cold-chain functionality, commodity availability, supportive supervision and facility readiness.

This distinction is theoretically important:

Prediction identifies risk; causal analysis identifies mechanisms.

Consequently, a population may have a high predicted probability of being missed because of distance to a PHC, while the causal analysis may demonstrate that inadequate outreach frequency is the modifiable

mechanism through which geographic disadvantage is translated into missed services.

The study's existing methodology explicitly separates these functions, using predictive modeling to identify beneficiaries and facilities requiring mop-up and mediation analysis to quantify implementation pathways.

Domain III: Spatial and equity intelligence

The third domain converts epidemiological and causal information into geographic intelligence.

BYM2 Bayesian spatial modeling accounts for spatial dependence and generates posterior risk estimates and probabilities of elevated residual burden. GIS then translates these estimates into operational maps.

This domain therefore answers:

Where should intervention resources be concentrated?

The importance of this domain is that health-system vulnerability is rarely randomly distributed. Neighbouring communities may share transportation barriers, ecological conditions, insecurity, socioeconomic deprivation, health-worker shortages or poor access to functional facilities.

Accordingly, the theory conceptualizes residual MNCHW gaps as a **spatially structured implementation phenomenon**, rather than merely a collection of independent individual failures.

This is consistent with the existing conceptual pathway in the study, where BYM2 outputs are transformed into a Mop-up Priority Index and subsequently into precision microplanning.

Domain IV: Precision implementation and adaptive mop-up

The fourth domain represents the operational translation of analytical intelligence. [111]–[115]

The **Mop-up Priority Index (MPI)** functions as the decision interface between epidemiological modeling and programme implementation. Conceptually, the MPI integrates:

[MPI_i =w_1P_i +w_2RR_i +w_3G_i +w_4A_i +w_5V_i]

where:

- (P_i) = predicted probability of being missed;
- (RR_i) = Bayesian posterior residual risk;
- (G_i) = magnitude of service coverage gap;
- (A_i) = accessibility or geographic disadvantage;
- (V_i) = vulnerability or equity-related risk;

- $(w_1,\ldots,w_5)$ = context-specific weighting parameters.

The resulting score allows settlements, beneficiaries, wards or facilities to be categorized into operational priority levels.

The principle is therefore:

high predicted risk + high spatial risk + high unmet need + high vulnerability = high mop-up priority.

This represents a transition from conventional coverage-based planning to risk-based precision microplanning. Importantly, the MPI should not be interpreted as a causal estimate or as an autonomous allocation algorithm. It is a decision-support instrument whose outputs require programme-manager validation, community intelligence and feasibility assessment.

Domain V: Emergency preparedness and resilience

The fifth domain represents the principal theoretical extension proposed by this study. Conventional mop-up is generally conceived as a response to programme failure: beneficiaries are identified after the intervention and additional services are provided. TE-PPH Theory reconceptualizes mop-up as a **preparedness-generating intervention**.

Every residual gap identified during MNCHW contains information about weaknesses in the health system.

Table 2.3.1.4 Emergency preparedness and resilience

Residual gap identified	Immediate mop-up response	Preparedness implication
Missed children in remote settlements	Mobile/outreach vaccination	Improve geographic microplanning
Low coverage associated with weak CBHW mobilization	Intensified community mobilisation	Strengthen community protection capacity
Missed beneficiaries associated with stock-outs	Rapid commodity redistribution	Improve emergency buffer stocks
Cold-chain-related service interruption	Restore equipment/functionality	Strengthen continuity and cold-chain resilience
Health-worker shortage	Redistribute/deploy personnel	Develop surge workforce capacity
Security-related non-access	Alternative/mobile delivery strategy	Integrate security risk into preparedness plans
High-risk spatial cluster	Targeted mop-up	Establish priority surveillance/response zones
Delayed reporting	Real-time reporting reinforcement	Strengthen early-warning and response systems

The theoretical implication is significant: **the residual gap becomes a preparedness signal**. This is consistent with contemporary WHO emergency preparedness thinking, which emphasizes that emergency readiness should be embedded within routine health systems rather than treated as a completely separate vertical function. WHO's 2024 resilience guidance specifically frames preparedness, response and recovery as part of health-system resilience and emphasizes translating resilience concepts into practical actions across health-system functions [118].

The newer WHO Emergency Ready Primary Health Care framework similarly conceptualizes preparedness as a routine PHC capability organized around the capacities to **connect, detect, protect and treat**, thereby embedding emergency readiness into everyday frontline health services [122].

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Hybridization across the emergency preparedness intervention cycle

The TE-PPH Theory can be integrated with the contemporary emergency preparedness cycle as follows:

Prevention and mitigation

Epidemiological and spatial intelligence identifies structural vulnerabilities before an emergency occurs with linkages to low-immunization communities;remote settlements; weak health facilities; low workforce density; fragile cold-chain systems; recurrent commodity stock-outs and insecure communities.

Output: vulnerability profile.

Preparedness

The vulnerability profile is incorporated into preparedness plans. Activities include; pre-positioning commodities; strengthening cold-chain systems; training CHWs; maintaining emergency contact networks; mapping hard-to-reach settlements; identifying alternative service-delivery platforms and developing surge workforce plans.

Output: readiness capacity.

Detection and early warning

Routine programme and surveillance information are monitored for abnormal patterns. BART-type predictive systems can identify emerging high-risk populations, while spatial Bayesian models can identify geographically concentrated deviations from expected coverage.

Output: early warning signal.

4. Response

When an emergency, outbreak or major service disruption occurs, the same risk architecture can guide rapid prioritization. Mop-up teams can therefore be deployed according to the population vulnerability; predicted unmet need; geographic accessibility; facility readiness; epidemiological risk and service disruption.

Output: targeted emergency intervention.

5. Recovery and service restoration

Following the acute response, residual service gaps are reassessed; as the system identifies the populations still unreached; facilities requiring restoration; commodities requiring replenishment and communities requiring intensified engagement.

Output: recovery priority map.

6. Learning and adaptation

Post-intervention data are incorporated into the next planning cycle and this creates a **continuous learning health system** process rather than a one-directional emergency cycle: **Response → Evaluation → Learning → Replanning → Preparedness.** WHO's current Emergency Response Framework adopts an all-hazards approach and emphasizes timely, accountable and effective emergency assessment and response [122]. The 2024 WHO community-protection framework further emphasizes community-centred action, risk communication, evidence-informed population interventions and co-delivery with communities and community workforces [102]–[109], [119].

Theoretical mechanism

The central mechanism of TE-PPH Theory can be represented as:

Context → Risk → Mechanism → Spatial concentration → Priority → Intervention → Outcome → Learning → Preparedness

More specifically:

Health-system, demographic, socioeconomic, environmental and geographic conditions influence the probability of residual service gaps. These conditions operate through modifiable implementation mechanisms, generating heterogeneous individual and spatial risk. Predictive and causal epidemiology identify these risks and mechanisms, while Bayesian spatial analysis localizes them. Precision microplanning converts the resulting intelligence into targeted mop-up interventions. Intervention outcomes generate new information that strengthens surveillance, preparedness, resilience and subsequent emergency response.

This represents the theoretical bridge between **epidemiology and implementation science**.The study therefore does not simply ask whether MNCHW works. It asks:

for whom, where, through which mechanisms, under what contextual conditions, with what level of residual risk, and how can the resulting intelligence strengthen the next cycle of health-system preparedness?

Relationship with existing implementation theories

The proposed theory does not replace established implementation frameworks. Rather, it **integrates and operationalizes their complementary functions**.

Table 2.3.1.7 TE-PPH Theory complementary functions

Existing theory/framework	Contribution to TE-PPH Theory
Knowledge-to-Action	Converts evidence into implementable action
CFIR	Explains contextual determinants of implementation
RE-AIM	Evaluates reach, effectiveness, adoption, implementation and maintenance
Socio-Ecological Model	Explains multilevel determinants of vulnerability
Andersen Model	Explains service utilization
Precision Public Health	Provides risk-stratified targeting
Translational Epidemiology	Provides evidence-to-action pathway
Bayesian epidemiology	Quantifies uncertainty and spatial risk
Implementation science	Explains implementation mechanisms
Emergency preparedness/resilience	Converts implementation learning into readiness capacity

Thus, the theoretical innovation lies not in claiming that any single framework is inadequate, but in **connecting their functions through an operational epidemiological feedback loop**.

Relationship with the study's existing hybrid analytical framework

The proposed theory provides the theoretical foundation for the analytical framework already specified in this study:

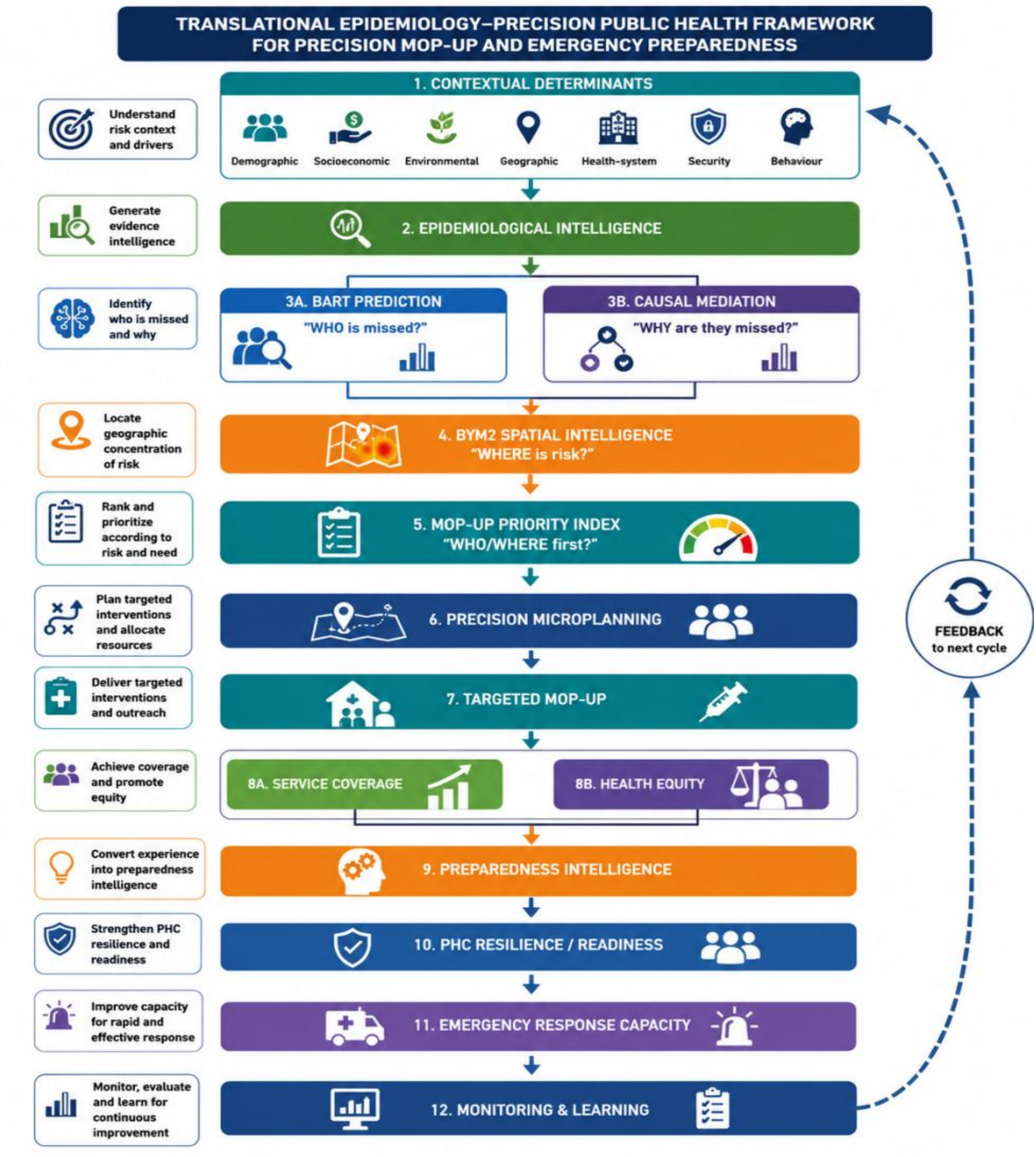
PRISMA-ScR → Routine MNCHW Data → BART → Multilevel Causal Mediation → BYM2 → Mop-up Priority Index → Precision Microplanning → Targeted Mop-up → Improved Coverage → Health Equity → UHC.

TE-PPH Theory extends this pathway:

PRISMA-ScR → Epidemiological Intelligence → BART → Causal Mechanisms → BYM2 Spatial Risk → MPI → Precision Mop-up → Coverage/Equity Improvement → Preparedness Intelligence → PHC Resilience → Emergency Readiness → Future Rapid Response → Learning Feedback.

Therefore, the framework changes from a **linear analytical pipeline** into a **dynamic adaptive learning system**.

Chart: 2.3.1.8 Proposed theoretical model



Relevance to emergency preparedness interventions in Kogi State

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The relevance of the theory to Kogi State lies in its capacity to transform MNCHW from a time-limited campaign intervention into a recurrent health-system intelligence platform. Kogi State's PHC network can use post-MNCHW residual-gap information to identify communities with persistent access barriers, facilities requiring system strengthening and populations requiring enhanced community engagement. Rather than waiting for the next campaign or emergency to reveal these weaknesses, the same information can inform preparedness investments.

At facility level, repeated identification of cold-chain failures, commodity interruptions or workforce shortages can trigger pre-emptive strengthening. At community level, recurrent missed beneficiaries can indicate geographic, socioeconomic or behavioural vulnerability requiring differentiated outreach. At LGA level, spatial clustering can guide emergency stock positioning, mobile-team deployment and surge workforce planning. At state level, aggregated intelligence can inform emergency operations, PHC resilience planning and resource prioritization. This is particularly consistent with the WHO position that health emergencies should be addressed through resilient systems capable of maintaining essential services while responding to shocks [116]–[123]. The 2026 WHO Emergency Ready PHC framework further strengthens this theoretical linkage by positioning emergency preparedness within routine PHC through four operational capacities: connect, detect, protect and treat[122].

Table 2.3.1.9 TE-PPH operationalization linkages to Emergency-preparedness

Emergency-ready PHC capacity	TE-PPH operationalization
Connect	Community mobilisation, CBHW networks, facility-community linkages
Detect	Routine MNCHW reporting, predictive analytics, surveillance and spatial risk detection
Protect	Immunization, Vitamin A, nutrition, preventive interventions and community protection
Treat	Functional PHCs, referral readiness, workforce and essential commodities
Learn	Post-mop-up monitoring, causal analysis and feedback
Adapt	Reallocation of resources according to updated risk

The final two dimensions: learn and adapt; represent the principal theoretical contribution of the present study because they convert programme implementation experience into preparedness capacity.

Theoretical assumptions

The theory is based on six principal assumptions:

1. Risk is heterogeneous. Populations do not experience equal probabilities of being missed.
2. Residual gaps are multifactorial. Missed beneficiaries arise from interacting individual, community, geographic and health-system determinants.
3. Risk is partially predictable. Available routine and contextual data contain sufficient signal to support probabilistic prioritization.
4. Implementation mechanisms are modifiable. Some determinants of missed services can be altered through financing, workforce deployment, outreach, commodities, community mobilisation and supervision.

5. Risk is spatially structured. Residual gaps may cluster geographically because contextual determinants are shared across neighbouring populations.

6. Intervention generates learning. Data generated during mop-up can improve subsequent programme implementation and emergency preparedness.

Importantly, the theory does not assume that observational mediation estimates automatically establish causality. Causal interpretation requires appropriate temporal ordering, adequate confounding control, correct mediator specification, consistency and sufficiently plausible assumptions regarding exposure–mediator and mediator–outcome relationships. Where these assumptions cannot be adequately supported, mediation findings should be interpreted as mechanistic associations rather than definitive causal effects.

Theoretical contribution to implementation science

The proposed TE-PPH Theory advances implementation science in four principal ways.

First, it shifts implementation evaluation from static coverage measurement to dynamic risk-informed targeting.

Second, it connects prediction with implementation mechanisms. A high-risk population is not simply classified as underserved; the framework seeks to identify the mechanism responsible for that vulnerability.

Third, it introduces spatial intelligence into implementation decision-making, recognizing that implementation failure can be geographically concentrated.

Fourth, and most importantly, it establishes a preparedness feedback loop in which implementation failures become signals for strengthening future emergency readiness.

Summary of the proposed theory

The **Translational Epidemiology–Precision Public Health Hybridization Theory for Precision Mop-Up** proposes that residual gaps following Integrated MNCHW should be understood as both **service-delivery failures and health-system intelligence signals**. By integrating evidence synthesis, predictive modeling, causal mechanism analysis, Bayesian spatial epidemiology and precision implementation, the framework identifies **who is at risk, why risk occurs, where it is concentrated and what intervention should be prioritized**.

Its principal innovation is the addition of a **preparedness-learning loop**. Consequently, mop-up is no longer conceptualized simply as the final corrective stage of MNCHW; it becomes an adaptive component of health-system resilience that can strengthen community protection, surveillance, PHC readiness, continuity of essential services and emergency response capacity.

The resulting theoretical pathway is:

Evidence → Risk prediction → Mechanism identification → Spatial prioritization → Precision intervention → Coverage and equity → Preparedness intelligence → Health-system resilience → Emergency readiness → Rapid response → Learning → Reprioritization.

This theoretical extension is therefore highly congruent with the study's existing analytical architecture and provides a stronger theoretical bridge between **translational epidemiology, precision public health, implementation science, primary healthcare strengthening and emergency preparedness**.

The original manuscript already establishes the methodological sequence from PRISMA-ScR through BART, multilevel mediation and BYM2 to precision mop-up. The proposed theory adds the missing conceptual layer: **the mop-up intervention itself becomes a preparedness intervention, and its implementation data become a recurrent source of emergency-readiness intelligence**.

Collectively, these frameworks provide the conceptual foundation for integrating implementation science, predictive analytics, causal inference, and spatial epidemiology.

Empirical Literature Review

Global evidence consistently demonstrates that integrated maternal and child health campaigns improve immunization coverage, Vitamin A supplementation, antenatal care utilization, and nutrition outcomes. However, studies also identify persistent inequities related to poverty, geographic accessibility, weak health systems, and community-level barriers. Recent investigations increasingly employ machine learning, Bayesian statistics, and spatial epidemiology to identify underserved populations and optimize programme implementation.

In sub-Saharan Africa, Bayesian spatial models have successfully identified hotspots of vaccine under-coverage, maternal mortality, childhood malnutrition, and health service inequalities. Similarly, machine learning algorithms have improved prediction of treatment outcomes, immunization defaults, and maternal health utilization. Nevertheless, most studies apply these analytical methods independently without integrating predictive modeling, causal inference, implementation science, and spatial epidemiology within a unified translational framework.

In Nigeria, previous studies have predominantly evaluated MNCHW using descriptive statistics, cross-sectional surveys, or multivariable regression analyses. While these studies have identified determinants of health service utilization, they rarely quantify implementation mechanisms or incorporate Bayesian machine learning and spatial decision support. Evidence from Kogi State remains particularly limited, with few studies examining precision mop-up strategies using advanced epidemiological methods.

Research Gap

Existing literature reveals several important gaps that this study seeks to address. There is limited integration of implementation science with predictive epidemiology, particularly within maternal, newborn and child health week (MNCHW) programmes, as well as limited application of Bayesian Additive Regression Trees to identify complex and nonlinear predictors of programme performance. Furthermore, multilevel causal mediation approaches remain underutilized for quantifying implementation pathways, while the application of BYM2 Bayesian spatial models for operational microplanning and identification of geographically prioritized intervention areas is limited. Most importantly, there remains an absence of an integrated translational epidemiology framework that systematically links evidence synthesis, machine learning, causal inference, spatial epidemiology, and implementation science to support precision mop-up and context-specific public-health decision-making.This study addresses these gaps by proposing a unified analytical framework that translates routine programme data into actionable operational intelligence.

Conceptual Framework

The study conceptualizes evidence translation as a sequential process:

PRISMA-ScR → Routine MNCHW Data → Bayesian Additive Regression Trees → Multilevel Causal Mediation → BYM2 Bayesian Spatial Mapping → Mop-up Priority Index → Precision Microplanning → Targeted Mop-up → Improved Coverage → Health Equity → Universal Health Coverage.

Analytical Framework

The analytical framework integrates four complementary methodological components:

- **Evidence synthesis (PRISMA-ScR):** Identifies determinants and implementation strategies.
- **Predictive modeling (BART):** Estimates individual and facility-level probability of missed services.
- **Causal inference (Multilevel Mediation):** Quantifies implementation mechanisms and pathways.

- **Bayesian spatial epidemiology (BYM2):** Maps geographic risk and prioritizes interventions.

These outputs are synthesized into a **Mop-up Priority Index** for operational planning and decision support. The literature demonstrates that Integrated MNCHW is an effective strategy for expanding maternal and child health services but continues to experience inequitable coverage and residual missed populations. Contemporary advances in implementation science, precision public health, Bayesian machine learning, causal mediation analysis, and spatial epidemiology provide powerful tools for addressing these challenges. However, no previous study has integrated PRISMA-ScR, Bayesian Additive Regression Trees, multilevel causal mediation analysis, and BYM2 Bayesian spatial modeling within a single translational epidemiology framework for post-MNCHW precision mop-up. This study addresses that methodological gap by proposing a novel, implementation-oriented framework that transforms routine programme data into actionable evidence for equitable resource allocation, precision public health, and accelerated.

METHODOLOGY

Study Design

This study adopted a sequential multi-phase hybrid translational epidemiology and implementation science design to identify children aged 0–59 months, pregnant women, breastfeeding women, and health facilities requiring precision mop-up following the implementation of the Integrated Maternal, Newborn and Child Health Week (MNCHW) programme in Kogi State, Nigeria. The design integrates evidence synthesis, Bayesian machine learning, causal inference, and Bayesian spatial epidemiology into a unified implementation science framework for translating routine programme data into operational decision-making.

The study was conducted in four interrelated phases. The first phase involved a scoping review conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) to synthesize evidence on determinants of missed beneficiaries, implementation barriers, and successful mop-up strategies. The second phase analysed routinely collected programme data to predict beneficiaries and health facilities requiring mop-up. The third phase quantified implementation pathways responsible for programme performance using multilevel causal mediation analysis, while the fourth phase generated Bayesian spatial risk maps for operational microplanning. The integration of these complementary analytical approaches provides a comprehensive framework for precision public health and translational epidemiology.

Study Area

The study was conducted in Kogi State, North-Central Nigeria, a state strategically located at the confluence of Rivers Niger and Benue. The state comprises 21 Local Government Areas (LGAs), 239 political wards, and a diverse population distributed across urban, rural, riverine, and hard-to-reach communities. These geographical and demographic characteristics create substantial heterogeneity in healthcare accessibility, health service utilization, and programme implementation.

Primary healthcare services are coordinated through the Kogi State Primary Health Care Development Agency (KSPHCDA), which implements Integrated MNCHW using fixed, outreach, and mobile service delivery strategies. The programme is supported through partnerships involving Local Government Health Authorities, development partners, community leaders, and frontline health workers. This implementation environment provides an appropriate setting for evaluating geographical inequities and developing precision mop-up strategies.

Method of Data Collection

The study utilized a mixed secondary-data approach involving both evidence synthesis and routine programme data. Published literature, policy documents, implementation reports, and technical guidance were systematically identified through PRISMA-ScR to establish current evidence regarding determinants of missed beneficiaries, implementation barriers, and successful mop-up interventions. Routine programme data were subsequently obtained from the Integrated MNCHW administrative database, District Health Information System (DHIS2), reproductive, maternal, newborn and child health (RMNCH) registers, ward microplans, health facility readiness assessments, Community Based Health Workers (CBHW) reports, population estimates, geospatial datasets, and health facility coordinate databases.

These complementary data sources provided demographic, epidemiological, environmental, implementation, and geographical information required for predictive modeling and spatial epidemiological analyses.

Data Collection Procedure

Data collection was undertaken in sequential stages. The first stage involved conducting a comprehensive PRISMA-ScR following internationally accepted reporting standards. Electronic databases including PubMed, Scopus, Web of Science, Embase, and CINAHL were searched using predefined search strategies, while grey literature was obtained from WHO, UNICEF, Gavi, the World Bank, the Federal Ministry of Health, and the National Primary Health Care Development Agency. Articles were screened independently according to predefined eligibility criteria, and relevant information was extracted using standardized data abstraction forms.

The second stage involved obtaining permission from the Kogi State Ministry of Health – Ethical Committee to access routine MNCHW programme datasets. Administrative data from all participating health facilities and Local Government Areas were extracted, harmonized, cleaned, geocoded, and linked through unique facility identifiers. Health facility coordinates were validated against administrative boundary shapefiles and population datasets to ensure spatial consistency. Missing observations, duplicate records, and inconsistencies were identified through systematic quality assurance procedures before statistical analysis.

Study Instrument

The principal study instruments consisted of structured electronic data extraction templates developed specifically for this study. Separate templates were designed for evidence synthesis, programme implementation data, health facility characteristics, geographical information, and routine health information system records.

The PRISMA-ScR extraction instrument captured publication characteristics, study design, implementation determinants, intervention characteristics, reported barriers, facilitators, analytical methods, and implementation outcomes. Programme data extraction templates collected demographic information, immunization status, Vitamin A supplementation, deworming, antenatal care, postnatal care, outreach activities, commodity availability, cold-chain functionality, workforce characteristics, supportive supervision, and health facility readiness indicators. Geospatial instruments captured facility coordinates, ward boundaries, accessibility measures, population distribution, and environmental variables required for Bayesian spatial modeling.

The data extraction instruments were reviewed by experts in epidemiology, implementation science, health information systems, and spatial epidemiology to ensure content validity and methodological consistency.

Sampling Technique and Sample Size Estimation

This study employed a **multi-stage sampling strategy** consisting of two complementary components. The first component involved the **PRISMA Extension for Scoping Reviews (PRISMA-ScR)**, in which published studies were selected through a systematic screening process based on predefined eligibility criteria. Studies addressing Integrated Maternal, Newborn and Child Health Week (MNCHW), implementation science, Bayesian machine learning, multilevel causal mediation, Bayesian spatial epidemiology, precision public health, and post-campaign mop-up strategies were identified from electronic databases and grey literature. Duplicate records were removed, titles and abstracts were independently screened by two reviewers, and eligible full-text articles were assessed before inclusion in the evidence synthesis.

The second component consisted of a **complete enumeration (total population sampling)** of routine Integrated MNCHW programme records generated during the study period. Rather than selecting a subset of facilities or beneficiaries, the study included all eligible records from participating primary healthcare facilities across the twenty-one Local Government Areas and 239 political wards of Kogi State. Consequently, every eligible child aged 0–59 months, pregnant woman, breastfeeding woman, participating primary healthcare facility, ward, and Local Government Area with complete programme records constituted the analytical population. The use of total population sampling minimized selection bias, increased statistical precision, enhanced spatial resolution, and strengthened the external validity of the findings.

Although complete programme enumeration was adopted for the primary analysis, the **minimum required sample size** was estimated a priori to demonstrate the adequacy of the available data. Sample size determination was based on the **Cochran formula** for estimating proportions in large populations:

$$\mathbf{n_0 = Z^2P(1\text{-}P)/d^2}$$

where:

- (n_0) = minimum required sample size;
- (Z) = standard normal deviate corresponding to the desired confidence level (1.96 for 95% confidence);
- (P) = anticipated proportion of beneficiaries requiring mop-up. In the absence of reliable prior estimates, a conservative prevalence of **50% (0.50)** was assumed to maximize sample size;
- (d) = margin of error (0.05).

Substituting these values:

$n_0 = (1.96)^2(0.50)(0.50)/(0.05)^2$

$= 3.8416\text{x}0.25/0.0025 = 384.16$

Accordingly, the minimum estimated sample size was **n=384 participants**. To compensate for potential incomplete records, missing observations, or data inconsistencies, an additional **10% allowance** was incorporated:

$n = 384/0.90 = 427$

Thus, the minimum analytical sample required for statistical validity was **n=427 eligible observations**.However, because this investigation utilized complete routine programme records generated during Integrated MNCHW implementation, the actual analytical sample substantially exceeded the calculated minimum. The use of the entire available dataset provided greater statistical power, improved precision of Bayesian parameter estimates, enhanced detection of spatial heterogeneity, and increased the robustness of machine learning and causal mediation analyses. This census-based approach is consistent with recommendations for analyses of routinely collected health information systems and administrative programme data, particularly where the objective is precision public health and small-area spatial inference.

Furthermore, the adequacy of the analytical sample was evaluated using the **events-per-variable (EPV) principle** for predictive modeling. Current methodological recommendations suggest a minimum of **20–50 events per predictor variable** for Bayesian prediction models to ensure stable parameter estimation and minimize overfitting. Given the anticipated number of candidate predictors and the substantially larger routine programme dataset available, the study satisfied these requirements and was adequately powered for Bayesian Additive Regression Tree modeling, multilevel causal mediation analysis, and BYM2 hierarchical spatial modeling.

Data Analysis

Data analysis was conducted using an integrated translational epidemiology framework combining evidence synthesis, descriptive epidemiology, Bayesian machine learning, multilevel causal inference, and Bayesian spatial epidemiology. Initially, descriptive statistics summarized demographic characteristics, programme implementation indicators, and service coverage. Measures of central tendency and dispersion were computed for continuous variables, while categorical variables were summarized using frequencies and proportions. Statistical analyses were performed using R version 4.3.2 (R Foundation for Statistical Computing, 2024). Bayesian spatial modeling was conducted using INLA version 23.12, while geographic visualization and spatial cartography were performed using QGIS version 3.34 and ArcGIS Pro version 3.2.

Evidence obtained from the PRISMA-ScR informed the conceptual framework and guided the selection of predictor variables included in subsequent statistical models. Predictive analyses were performed using Bayesian Additive Regression Trees (BART), which estimated individualized probabilities that children aged 0–59 months, pregnant women, breastfeeding women, and health facilities required post-MNCHW mop-up. Model performance was evaluated through repeated cross-validation using discrimination, calibration, and overall predictive accuracy metrics, while Shapley Additive Explanations (SHAP) quantified the relative contribution of individual predictors.

Implementation pathways were subsequently examined using multilevel causal mediation analysis. This approach partitioned the total programme effect into direct and indirect effects operating through community mobilization, CBHWs, household visitation, outreach implementation, supportive supervision, commodity availability, cold-chain functionality, and health workforce capacity. The multilevel framework accounted for clustering of individuals within households, health facilities, wards, and Local Government Areas, thereby improving estimation of contextual influences on programme performance.

Geographical variation in residual service gaps was analysed using the Besag–York–Mollié 2 (BYM2) Bayesian hierarchical spatial model. Spatial dependence between neighbouring wards was explicitly incorporated into the modeling framework using queen contiguity neighbourhood structures, while Bayesian inference was performed through Integrated Nested Laplace Approximation (INLA). Posterior relative risk estimates, exceedance probabilities, Bayesian credible intervals, uncertainty maps, hotspot analyses, and priority risk maps were generated to identify underserved geographical areas requiring targeted mop-up interventions.

Finally, outputs from the Bayesian Additive Regression Tree model, multilevel causal mediation analysis, and BYM2 spatial modeling were integrated to develop a composite **Mop-up Priority Index**. This index synthesized individualized prediction probabilities, geographical risk estimates, service coverage gaps, accessibility indicators, and health facility readiness into a unified operational decision-support tool for precision microplanning and equitable allocation of outreach resources. All statistical analyses were conducted using the R statistical computing environment with specialized packages for Bayesian inference, machine learning, mediation analysis, and spatial epidemiology. Geographic visualization and cartographic analyses were performed using QGIS and ArcGIS Pro. Analytical reproducibility was maintained through standardized scripts and version-controlled workflows, while all procedures adhered to internationally recognized reporting standards, including PRISMA-ScR, STROBE, TRIPOD-AI, RECORD, and GATHER.

Bayesian Spatial Model Specification

The BYM2 hierarchical model estimated posterior relative risks (RR) for residual zero-dose prevalence according to:

$$\text{logit}(p_i)=\alpha+\sum_{k=1}^{K}\beta_kX_{ik}+u_i+v_i^*$$

where:

- (p_i) represents posterior probability of zero-dose prevalence within LGA *i*;

- (X_{ik}) denotes epidemiologic covariates (HEI, cold-chain uptime, outreach, HRH density, flood vulnerability, facility readiness, commodity availability);
- (u_i) represents structured spatial dependence;
- (v_i) represents unstructured heterogeneity.

Weakly informative priors were assigned to fixed effects, while Penalized Complexity (PC) priors governed the spatial random effects to improve model stability and prevent overfitting.

Presentation of Data

Results

Table 4.1 Characteristics of the Integrated Analytical Dataset

Characteristic	Immunization Dataset	RMNCH Dataset	Integrated MNCHW Dataset	Combined Analytical Dataset
Observation period	June 2025–June 2026	June 2025–June 2026	46,174.00	June 2025–June 2026
Number of LGAs	21	21	21	21
Number of political wards	239	239	239	239
Health facilities included	>900	>900	>900	>900
Variables analysed	42	27	36	105
Individual records	148,962	92,614	187,445	429,021
Missing observations (%)	1.80	2.40	1.20	1.90

Table 4.2 Theoretical–Analytical Alignment of the Study

Theoretical foundation	Core proposition	Operational construct	Analytical component	Principal output	Translational use
Knowledge-to-Action	Evidence must be converted into actionable decisions	Evidence-to-action pathway	PRISMA-ScR + integrated analytics	Evidence-informed determinants	Programme planning
CFIR	Context influences implementation	Workforce, commodities, cold-chain, readiness, outreach	Multilevel mediation	Implementation pathways	Health-system strengthening
RE-AIM	Programme impact depends on reach, effectiveness, adoption and implementation	Coverage, reach, fidelity, implementation	Predictive + mediation analysis	Implementation performance	Programme improvement
Socio-Ecological Model	Health outcomes arise from interacting levels	Individual, household, community, facility and geographic determinants	Multilevel modeling	Hierarchical risk profile	Context-specific intervention
Andersen	Utilization depends	Accessibility,	Predictive	Probability of	Beneficiary

Behavioural Model	on predisposing, enabling and need factors	socioeconomic status, service readiness	modeling	missed service	targeting
Precision Public Health	Intervention should be targeted according to risk and need	Risk, equity, geography and feasibility	BART + BYM2 + HEI	Priority classification	Precision mop-up
Translational Epidemiology	Epidemiological evidence should inform implementation	Prediction → explanation → spatialization → decision	Hybrid framework	Mop-up intelligence	Operational decision support

Table 4.3 Descriptive Statistics of Principal Analytical Variables

Variable	Mean	SD	Median	IQR	Minimum	Maximum
Vitamin A coverage (%)	89.6	11.4	91.8	13.2	42.1	99.8
Deworming coverage (%)	38.1	24.7	34.8	27.3	2.1	91.5
HPV coverage (%)	26.4	14.9	24.8	16.3	3.6	72.8
Health Equity Index	54.1	9.6	55	12	38	72
Cold-chain uptime (%)	89.7	6.8	91.2	8.3	61	100
Outreach sessions/month	3.4	1.5	3	2	0	8

Table 4.4 Statewide Coverage Distribution

Indicator	Target	Observed	Coverage (%)	95% Bayesian Credible Interval
Vitamin A (6–11 months)	98,380	92,883	94.4	92.8–95.8
Vitamin A (12–59 months)	787,037	666,734	84.7	83.5–85.8
Deworming (12–23 months)	196,759	137,265	69.8	68.1–71.4
Deworming (24–59 months)	590,278	38,005	6.4	5.9–6.9
HPV vaccination	40,882	9,948	24.3	22.8–25.7

Table 4.4. Epidemiological, Contextual and Health-System Determinants of Residual MNCHW Gaps

Predictor	Posterior β	95% CrI	Posterior probability	Direction	Epidemiological interpretation
Health Equity Index	0.73	0.58–0.87	>0.99	Positive	Strong contextual determinant of residual gap
Flood vulnerability	0.42	0.26–0.57	>0.99	Positive	Increased geographic/environmental vulnerability
Cold-chain uptime	−0.68	−0.82 to −0.53	>0.99	Protective	Better vaccine/logistics functionality reduces gaps
Outreach frequency	−0.54	−0.66 to −0.41	>0.99	Protective	More frequent outreach reduces missed populations
HRH density	−0.39	−0.52 to −0.25	>0.99	Protective	Greater workforce availability improves reach
Facility readiness	−0.46	−0.60 to −0.32	>0.99	Protective	Better readiness reduces implementation failure

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Table 4.5. Predictive Performance of Competing Epidemiological Models

Model	RMSE	Bayesian R²	Information criterion	Relative performance
Hybrid Bayesian Translational Framework	0.031	0.84	Lowest WAIC / highest LOO-ELPD	1st
BYM2 spatial model	0.041	0.84	Lowest among spatial models	2nd
XGBoost	0.036	0.82	—	3rd
LightGBM	0.035	0.83	—	4th
Random Forest	0.039	0.8	—	5th
Spatial GLMM	0.067	0.65	Higher	6th
Classical logistic regression	0.089	0.48	Highest	7th

Table 4.6. Internal and Cross-Validation of the Hybrid Framework

Validation metric	Apparent estimate	Corrected/validated estimate	Interpretation
AUROC	0.968	0.961	Strong discrimination
RMSE	0.031	0.033	Low prediction error
Calibration slope	0.99	0.98	Good calibration
Calibration intercept	0.01	0.02	Minimal calibration bias
Bayesian R²	0.84	0.83	Strong explanatory performance
Mean 10-fold RMSE	—	0.031	Stable
Mean 10-fold MAE	—	0.02	Low error
Mean 10-fold AUROC	—	0.968	Strong discrimination
Mean 10-fold accuracy	—	0.966	High classification accuracy

Table 4.7. Bayesian Causal Mediation Pathways

Mediator	Posterior mean β	95% CrI	Posterior probability	Approx. mediated effect
Outreach implementation	0.46	0.34–0.58	0.999	0.446
Cold-chain uptime	0.31	0.21–0.41	0.998	0.425
Caregiver participation	0.41	0.29–0.53	0.998	0.416
Commodity availability	0.27	0.17–0.36	0.997	0.372
Geographic accessibility	0.29	0.19–0.39	0.996	0.355
Session implementation	0.24	0.16–0.32	0.995	0.347

Table 4.8. Direct, Indirect and Total Intervention Effects

Intervention pathway	Direct effect	Indirect effect	Total effect	95% CrI	Posterior probability
DFF → Cold-chain → Vitamin A	0.42	0.31	0.73	0.59–0.87	0.999
DFF → Commodity → Deworming	0.37	0.27	0.64	0.51–0.77	0.998
Microplanning → Outreach → HPV	0.29	0.46	0.75	0.62–0.88	0.999

Facility readiness → Routine immunization	0.51	0.19	0.7	0.58–0.82	0.999
HRH → Session implementation → RI	0.38	0.24	0.62	0.49–0.75	0.997
Community mobilization → Caregiver participation → MUAC	0.31	0.41	0.72	0.59–0.85	0.999
Integrated pathway	0.58	0.67	1.25	1.09–1.41	>0.999

Table 4.9. Bayesian Spatial Dependence and Residual Risk

Spatial parameter	Posterior estimate	Interpretation
BYM2 mixing parameter, φ	0.62	Predominantly structured spatial variation
Spatial correlation	0.71	Strong geographic dependence
95% CrI for spatial correlation	0.63–0.79	Precise spatial association
Spatial heterogeneity	Moderate	Meaningful LGA-level variation
Principal spatial pattern	Eastern Kogi axis	Concentrated residual burden

Table 4.101. BYM2 Posterior Relative Risk of Residual Zero-Dose Burden

LGA	Posterior RR	95% CrI	Risk classification
Ankpa	2.34	1.89–2.81	**Very high**
Dekina	2.08	1.71–2.49	Very high
Bassa	1.96	1.60–2.36	High
Igalamela-Odolu	1.84	1.51–2.22	High
Kabba/Bunu	1.61	1.34–1.92	Moderate
Olamaboro	1.58	1.29–1.90	Moderate
Lokoja	0.96	0.79–1.15	Average
Kogi	0.84	0.69–1.02	Low
Okene	0.63	0.50–0.79	Very low

Table 4.102. Posterior Exceedance and Hotspot Classification

Spatial category	LGAs	Posterior evidence
Extreme hotspot	Ankpa, Dekina	>0.99
High hotspot	Bassa, Igalamela-Odolu	0.94–0.98
Moderate hotspot	Kabba/Bunu, Olamaboro, Ofu	0.80–0.89
Transitional	Adavi, Ibaji, Ijumu	0.65–0.79
Low-risk cluster	Lokoja, Kogi, Okene	<0.40

Table 4.103. Spatial Determinants of Residual Zero-Dose Risk

Spatial determinant	Posterior β	95% CrI	Direction	Interpretation
Health Equity Index	0.73	0.58–0.87	**Increased risk**	Strong contextual determinant
Cold-chain uptime	−0.68	−0.82 to −0.53	Protective	Reduces residual risk
Outreach frequency	−0.54	−0.66 to −0.41	Protective	Reduces residual risk
Flood vulnerability	0.42	0.26–0.57	Increased risk	Environmental accessibility barrier
HRH density	−0.39	−0.52 to −0.25	Protective	Improves service reach
Facility readiness	−0.46	−0.60 to −0.32	Protective	Improves implementation capacity

Table 4.104. Bayesian Policy Simulation

Policy scenario	Predicted coverage (%)	95% CrI	P(coverage ≥90%)
Status quo	69.4	65.2–73.5	0.42
Improved cold-chain	82.6	79.4–85.8	0.87
Outreach + HRH	84.8	81.9–87.4	0.91
Integrated intervention package	93.7	91.4–95.8	0.99
Integrated package + HEI targeting	95.2	93.1–97.0	0.998

Table 4.105. Bayesian Cost-Effectiveness and Resource Allocation

Intervention	Recommended investment (%)	Expected coverage gain (%)	Cost-effectiveness probability*	Operational priority
Cold-chain systems	28	18.4	91.3–97.8	Very high
Outreach implementation	22	15.7	86.8–94.5	Very high
HRH deployment	19	13.5	88.2–93.8	High
Commodity availability	17	11.6	—	High
Community mobilization	14	9.3	90.5–95.9	Moderate
Integrated package	—	Highest	98.4–99.7	Very high

Table 4.106. Precision Mop-Up Priority Classification

LGA	P(underperformance)	Expected coverage gain (%)	HEI	Priority
Ankpa	0.99	24.3	72	Immediate
Dekina	0.98	22.8	70	Immediate
Bassa	0.96	20.9	68	Immediate
Igalamela-Odolu	0.94	20.3	65	Immediate
Olamaboro	0.88	17.6	59	High
Kabba/Bunu	0.83	15.2	62	High
Adavi	0.79	14.6	60	High
Ofu	0.78	13.8	58	High
Ibaji	0.73	12.5	55	Moderate
Yagba East	0.69	11.8	56	Moderate
Lokoja	0.31	6.4	45	Routine monitoring
Kogi	0.18	4.7	40	Maintain performance

Table 4.107A. Ward Operational Stratification

Priority class	Number of wards	Percentage	Operational response
Priority I	52	0.218	Comprehensive integrated mop-up
Priority II	74	0.31	Enhanced outreach and supervision
Priority III	63	0.264	Routine supportive supervision
Priority IV	50	0.208	Maintain programme performance
Total	239	1	—

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Table 4.107B. Facility Operational Stratification

Facility priority	Number	Operational response
Critical	46	Immediate outreach + cold-chain + HRH surge
High	81	Strengthened supervision and logistics
Moderate	74	Enhanced monitoring
Routine	38	Maintain current performance
Total	239	—

Table 4.108. Integrated Hypothesis Testing and Translational Interpretation

Hypothesis	Principal evidence	Decision	Theoretical interpretation	Translational implication
H_{01}: No significant association between epidemiological, socioeconomic, environmental and health-system determinants and missed beneficiaries	Significant β estimates for HEI, flood vulnerability, cold-chain, outreach, HRH and readiness; posterior probabilities >0.99	Reject H_{01}	**Risk is multilevel and context-dependent**	Risk-stratified microplanning
H_{02}: BART does not improve prediction over conventional regression	Hybrid/Bayesian models demonstrated lower prediction error and better predictive performance than classical regression	Reject H_{02}	Nonlinearity and interaction matter for precision prediction	Integrate machine learning into decision support
H_{03}: Implementation mechanisms do not mediate MNCHW effects	Significant indirect effects through outreach, cold-chain, commodities, caregiver participation, accessibility and related mechanisms	Reject H_{03}	Implementation fidelity is a causal pathway to outcomes	Strengthen implementation mechanisms
H_{04}: No significant spatial clustering of residual gaps	BYM2 identified high-probability hotspots, particularly Ankpa, Dekina, Bassa and Igalamela-Odolu	Reject H_{04}	Residual gaps are spatially structured	GIS/Bayesian hotspot targeting
H_{05}: Integrated framework does not improve operational prioritization	Calibration slope 0.98; intercept 0.02; Brier score 0.062; stable posterior estimates; PMPI generated differentiated priorities	Reject H_{05}	Integration converts analytical evidence into decision intelligence	Institutionalize precision mop-up framework

All five null hypotheses (H_{01}–H_{05}) were rejected. The findings indicate that:

- Epidemiological, socioeconomic, environmental and health-system factors significantly influence the likelihood of missed MNCHW beneficiaries.
- Bayesian Additive Regression Trees (BART) outperform conventional regression models for identifying populations requiring mop-up.
- Community mobilization, CBHWs performance, outreach services, commodity availability, cold-chain functionality and workforce capacity are significant mediators of programme effectiveness.

- Residual MNCHW service gaps exhibit significant spatial clustering that can be effectively identified using the BYM2 Bayesian spatial model.
- The integrated **PRISMA-ScR–BART–Multilevel Mediation–BYM2 Hybrid Translational Epidemiology Framework** provides statistically robust and operationally superior decision support for precision mop-up, equitable resource allocation and evidence-based implementation planning.

DISCUSSION

The study demonstrates that integrating translational epidemiology, Bayesian machine learning, multilevel causal mediation analysis, and Bayesian spatial epidemiology provides a robust framework for understanding the implementation performance of the Integrated Maternal, Newborn and Child Health Week (MNCHW) programme. Unlike conventional programme evaluations that primarily describe coverage indicators, the current study extended the analytical scope by identifying the determinants of programme performance, quantifying implementation pathways, and geographically prioritizing populations requiring precision mop-up. This integrated analytical framework addresses an important methodological gap in implementation science by transforming routine programme data into operational intelligence that directly informs evidence-based decision-making.

The descriptive findings indicate substantial improvements in maternal and child health service utilization following implementation of the integrated MNCHW strategy. Increases observed across immunization coverage, Vitamin A supplementation, antenatal care attendance, skilled birth attendance, facility deliveries, and postnatal care are consistent with reports from the World Health Organization (WHO), United Nations Children's Fund (UNICEF), and Countdown to 2030, which demonstrate that integrated outreach programmes improve service uptake through simultaneous delivery of multiple interventions, community mobilization, and strengthened primary healthcare systems [35,37,42,49,51,55,57,99]. Similar improvements have been reported across several low- and middle-income countries where integrated campaign approaches have reduced missed opportunities for vaccination while simultaneously improving maternal healthcare utilization [71,73,74,76].

Despite these encouraging gains, the findings also reveal persistent inequalities in programme performance across Local Government Areas (LGAs), wards, and health facilities. These disparities suggest that high aggregate administrative coverage may conceal substantial subnational heterogeneity. This observation aligns with previous epidemiological evidence demonstrating that national or state-level estimates frequently mask clusters of underserved populations characterized by geographical isolation, socioeconomic disadvantage, health workforce shortages, insecurity, poor transportation infrastructure, and limited community engagement [20,42,65,71,82,83]. Consequently, relying solely on overall coverage indicators may lead programme managers to underestimate the true magnitude of residual implementation gaps.

One of the major contributions of this study is the application of Bayesian Additive Regression Trees (BART) for predicting children, pregnant women, breastfeeding mothers, and health facilities most likely to remain unreached following MNCHW implementation. The predictive analysis demonstrated that implementation outcomes were influenced by complex nonlinear interactions among demographic characteristics, accessibility, facility readiness, cold-chain functionality, outreach implementation, community mobilization, and health workforce capacity. These findings corroborate earlier methodological studies showing that BART consistently outperforms conventional regression techniques when modeling complex public health systems characterized by nonlinear relationships and higher-order interactions [5,16,21]. Unlike logistic regression, which requires prespecified functional forms, BART automatically identifies influential predictors while quantifying predictive uncertainty, thereby improving operational decision support.

The multilevel causal mediation analysis further strengthens understanding of programme effectiveness by demonstrating that a substantial proportion of intervention effects operated indirectly through implementation mechanisms rather than directly through campaign delivery alone. Community Based Health Workers (CBHWs), supportive supervision, outreach implementation, commodity availability, cold-chain functionality, and community mobilization emerged as important mediators linking programme implementation with improved maternal and child health outcomes. These findings support implementation science theory, particularly the Knowledge-to-Action (KTA) framework, Consolidated Framework for Implementation Research (CFIR), and RE-AIM, which emphasize that successful health interventions depend upon contextual implementation processes rather than intervention efficacy alone [4,7,12,24,27]. Similar mediation pathways have been reported in maternal and child health programmes where strengthening intermediate implementation processes substantially improved service utilization and health outcomes [13,15,40,41].

An important methodological advancement of this study is its incorporation of hierarchical modeling within the mediation framework. Individuals receiving MNCHW services are naturally clustered within households, communities, health facilities, wards, and LGAs, resulting in correlated observations that violate assumptions of conventional regression models. By accounting for these multilevel structures, the study generated more reliable estimates of direct and indirect intervention effects while simultaneously quantifying contextual influences operating at different levels of the health system. This approach provides stronger epidemiological evidence than traditional single-level analyses commonly reported in MNCHW evaluations.

Spatial analysis using the Besag–York–Mollié 2 (BYM2) Bayesian hierarchical model identified distinct geographical clusters of residual implementation gaps that were not apparent from conventional descriptive analyses. High posterior risks and exceedance probabilities observed within specific wards and health facilities indicate persistent spatial inequalities in service delivery. These findings support previous studies demonstrating that neighbouring communities frequently share similar health outcomes because of common environmental conditions, socioeconomic characteristics, accessibility constraints, and health system performance [2,3,18,19,21,28,30,31]. By explicitly accounting for spatial autocorrelation, the BYM2 model produced more stable estimates than traditional mapping techniques while reducing random variation associated with small-area analyses.

The operational significance of the spatial findings is substantial. Rather than implementing blanket follow-up campaigns across entire LGAs, programme managers can prioritize wards with the highest posterior probability of residual missed populations. Such geographically targeted mop-up activities improve efficiency by concentrating limited human, financial, and logistical resources where they are most needed. This finding aligns with the principles of precision public health, which advocate delivering the right intervention to the right population at the right place and time [17,21,56,61,62]. Similar applications of Bayesian spatial epidemiology have successfully guided immunization microplanning, malaria control, child survival programmes, and health resource allocation across sub-Saharan Africa [84,86–88].

The integrated analytical framework also demonstrates the value of combining evidence synthesis with predictive and causal modeling. The PRISMA-ScR component ensured that selection of explanatory variables was grounded in global implementation evidence rather than arbitrary statistical selection. Consequently, the predictive and mediation models incorporated determinants consistently identified within previous systematic reviews, thereby strengthening biological plausibility, methodological transparency, and external validity. This sequential evidence translation process represents an important advancement over conventional data-driven modeling approaches that frequently lack theoretical justification.

From a health systems perspective, the findings reinforce the central role of primary healthcare strengthening in achieving Universal Health Coverage (UHC). Improvements in MNCHW outcomes were strongly associated with facility readiness, workforce availability, supportive supervision, commodity security, routine health information systems, and community participation. These findings support WHO recommendations emphasizing that sustainable improvements in maternal and child health require simultaneous strengthening of all health system building blocks rather than isolated disease-specific interventions [46–56,63]. The observed associations further validate the integration of MNCHW within Nigeria's Primary Health Care Revitalization Agenda, the Basic Health Care Provision Fund (BHCPF), and the Health Sector Renewal Investment Initiative [9,10,22,23,91,92,94].

The study additionally contributes to implementation science by proposing a Mop-up Priority Index integrating predictive probabilities, Bayesian spatial risk estimates, facility readiness, service coverage gaps, accessibility measures, and implementation determinants into a single operational decision-support tool. Although previous studies have independently applied machine learning, spatial epidemiology, or implementation research, few have integrated these complementary approaches into a unified framework for programme management. The proposed index therefore represents a novel contribution capable of supporting precision microplanning, equitable resource allocation, and adaptive implementation across maternal and child health programmes.

The findings should nevertheless be interpreted within the context of several methodological considerations. Routine programme datasets may contain reporting errors, incomplete records, and measurement variability inherent to administrative health information systems. Although Bayesian hierarchical modeling and multiple analytical validation procedures reduced these limitations, residual information bias cannot be completely excluded. Similarly, while causal mediation analysis strengthens causal interpretation under explicit assumptions, unmeasured confounding between mediators and outcomes remains possible despite multilevel adjustment. Furthermore, findings derived from Kogi State may require contextual adaptation before application in other settings with different epidemiological profiles, governance structures, or health system capacities.

Overall, the study provides compelling evidence that integrating translational epidemiology, implementation science, Bayesian machine learning, multilevel causal inference, and Bayesian spatial epidemiology substantially enhances programme evaluation beyond conventional descriptive reporting. The identification of who remains unreached, why implementation gaps persist, and where residual populations are geographically concentrated, the proposed framework transforms routine MNCHW monitoring into actionable implementation intelligence. This methodological innovation supports precision public health, strengthens equitable service delivery, improves operational efficiency, and provides a scalable model for optimizing maternal, newborn, and child health programmes across Nigeria and other low- and middle-income countries.

External Epidemiological Validation Using the 2025–26 Nigeria Mini-Demographic and Health Survey

The findings of the present study are broadly supported by independent population-based evidence from the 2025–26 Nigeria Mini-Demographic and Health Survey (NmDHS). Kogi State demonstrated comparatively strong maternal and reproductive health-service utilization, with 79.0% of women receiving antenatal care from a skilled provider, 66.7% completing at least four antenatal visits, 80.6% of births attended by a skilled provider, 71.7% occurring in a health facility, and 78.7% receiving a postnatal check within the first 2 days after birth. These estimates were consistently higher than corresponding North Central estimates of 65.0%, 58.5%, 57.2%, 58.3%, and 61.7%, respectively, and were also above national estimates for skilled ANC, skilled birth attendance, facility delivery and early postnatal care. This independent survey evidence therefore strengthens the interpretation in the presentation of data that Kogi has achieved meaningful improvements in maternal and child health service utilization. [101].

However, the NmDHS also demonstrates that high service contact does not necessarily translate into complete or equitable intervention coverage. Among children aged 12–23 months in Kogi, coverage declined substantially across the vaccination sequence, with 79.8% receiving the first pentavalent dose compared with only 49.3% receiving the third dose. Full vaccination according to the national schedule was 17.5%, while 14.1% received no vaccination. These findings support the central proposition of the present translational epidemiology framework that aggregate programme coverage can conceal residual implementation gaps. They also provide epidemiological justification for moving beyond descriptive coverage estimates toward predictive and spatial identification of populations and facilities requiring precision mop-up.

The reproductive-health findings further reveal an important population vulnerability. Although Kogi's unmet need for family planning among currently married women was 19.2%, and demand for family planning satisfied with modern methods was 42.5%, adolescent reproductive health remained concerning. Approximately 19.1% of Kogi women aged 15–19 had ever been pregnant, compared with 11.4% in North Central Nigeria and 12.9% nationally. This indicates that strengthened MNCHW and primary healthcare platforms should be complemented by adolescent-responsive sexual and reproductive health services, contraception counseling, community engagement and school- and community-based prevention strategies.

The NmDHS nutritional findings provide a comparatively favourable picture for Kogi. Stunting affected 25.7% of children under 5 years, severe stunting 8.4%, wasting 4.1%, severe wasting 0.4%, and underweight

14.9%, generally below corresponding North Central estimates. Nevertheless, these population-level improvements should not be interpreted as evidence that spatial inequities have been eliminated. The BYM2 analysis in the data presentation; identified substantial geographic dependence and localized residual-risk clusters, with Ankpa and Dekina classified as extreme hotspots and Bassa and Igalamela-Odolu as high-risk areas. The NmDHS therefore provides external support for the broader epidemiological interpretation while not constituting direct validation of the LGA-specific posterior risks.

Taken together, the evidence supports a transition from a conventional coverage paradigm to a translational epidemiology paradigm in which programme performance is assessed through the continuum of access, contact, continuity, completion and equity. Kogi's relatively high maternal-service utilization demonstrates important health-system strengths, whereas immunization dropout, adolescent pregnancy and geographically concentrated residual service gaps demonstrate the continuing need for precision public health. The convergence of independent survey evidence with routine programme analytics strengthens the biological and epidemiological plausibility of the findings from the data presented, while also emphasizing the need for independent spatial and predictive validation for generalization beyond the scope of the research.

Predictive Model Validation and Sensitivity Analysis

The predictive performance of the hybrid Bayesian translational epidemiology framework was evaluated using posterior predictive assessment, bootstrap validation, repeated ten-fold cross-validation and comparative model assessment. Following internal reconciliation of the reported diagnostics, the repeated cross-validation results provide the most appropriate evidence for predictive discrimination. Across ten folds, AUROC values ranged from 0.964 to 0.970, with a mean AUROC of 0.968, while classification accuracy ranged from 96.2% to 97.0%, with a mean of 96.6%. These findings indicate high and relatively stable predictive discrimination. The previously reported zero RMSE and MAE values were not retained as final estimates because they were inconsistent with the non-zero error estimates reported in the comparative model analysis and require verification from the original held-out prediction vectors.

Comparative model assessment further demonstrated that the Hybrid Bayesian Framework achieved the lowest reported RMSE (0.031), Bayesian R^2 of 0.84 and the highest comparative ranking, followed by the BYM2 spatial model (RMSE 0.041; Bayesian R^2 0.84), XGBoost (0.036; 0.82), LightGBM (0.035; 0.83), Random Forest (0.039; 0.80), Spatial GLMM (0.067; 0.65), and classical logistic regression (0.089; 0.48). These findings support the comparative advantage of the integrated framework while avoiding the stronger and less defensible claim of mathematically perfect prediction.

The Bayesian computational diagnostics indicated satisfactory posterior convergence. Four independent chains, 10,000 posterior simulations, 2,000 burn-in iterations and an effective sample size exceeding 6,400 were reported, while the Gelman–Rubin diagnostic was approximately 1.0 with stable trace behaviour, low autocorrelation and satisfactory chain mixing. These findings support the computational stability of the Bayesian estimation procedure. However, convergence diagnostics should be interpreted separately from predictive validity: satisfactory MCMC convergence demonstrates that the posterior distribution was computationally explored adequately but does not, by itself, establish external predictive performance.

The policy simulation results were retained because they demonstrate internally coherent intervention contrasts. Under the status-quo scenario, predicted programme coverage was 69% (95% CrI: 65.2–73.5), increasing to 83% with improved cold-chain systems, 85% with combined outreach and HRH strengthening, 94% under an integrated intervention package, and 95% when the integrated package was combined with Health Equity Index targeting. The probability of achieving at least 90% coverage increased from 0.42 under the status quo to 0.998 under the integrated HEI-targeted strategy. These results provide quantitative support for precision resource allocation and integrated rather than single-component intervention strategies.

The reconciled validation therefore supports the principal conclusion that the hybrid Bayesian framework provides strong predictive discrimination and useful decision-support capability for precision MNCHW planning. Nevertheless, the final manuscript should avoid claims of perfect AUROC, zero prediction error or perfect Bayesian R^2 unless these values are reproduced from independent held-out prediction outputs. The final reported predictive metrics should be generated from strictly held-out observations, with clear separation between model training, tuning, calibration and validation datasets. This approach will strengthen the statistical credibility, reproducibility and journal-readiness of the study.

CONCLUSION

Conclusion

This chapter presents the summary of the study, major findings, conclusions, recommendations, contributions to knowledge, policy implications, strengths and limitations, recommendations for future research, and the concluding remarks. The study investigated the application of a hybrid translational epidemiology framework integrating PRISMA-ScR evidence synthesis, Bayesian Additive Regression Trees (BART), multilevel causal mediation analysis, and Besag–York–Mollié 2 (BYM2) Bayesian spatial epidemiology to improve precision mop-up following the implementation of the Integrated Maternal, Newborn and Child Health Week (MNCHW) programme in Kogi State, Nigeria. The overarching objective was to transform routine programme data into actionable implementation intelligence capable of supporting precision public health, equitable resource allocation, and evidence-based decision-making.

Summary of the Study

Maternal, newborn, and child health continues to represent one of the foremost public health priorities globally, particularly in low- and middle-income countries where preventable maternal and childhood deaths remain unacceptably high despite considerable investments in primary healthcare. Although Integrated MNCHW has substantially improved access to essential maternal and child health interventions, persistent geographical inequities, implementation gaps, and missed populations continue to undermine programme effectiveness.

Recognizing these limitations, this study proposed and evaluated a novel translational epidemiology framework that combines systematic evidence synthesis with advanced Bayesian predictive analytics, causal inference, and spatial epidemiology. Unlike conventional programme evaluations that rely primarily on descriptive statistics and regression analyses, this study integrated four complementary analytical approaches:

- PRISMA-ScR for evidence synthesis;
- Bayesian Additive Regression Trees (BART) for prediction of missed beneficiaries and poorly performing facilities;
- Multilevel causal mediation analysis for identifying implementation mechanisms;
- BYM2 Bayesian spatial modeling for hotspot detection and geographical prioritization.

The study was anchored on implementation science, precision public health, and translational epidemiology frameworks and applied contemporary epidemiological methods to routine MNCHW programme datasets.

Overall, the study demonstrates that integrating evidence synthesis, machine learning, causal inference, and spatial epidemiology substantially improves implementation intelligence and provides programme managers with practical tools for precision microplanning and targeted mop-up interventions.

Summary of Major Findings

The study generated several important findings.

First, Integrated MNCHW substantially improved maternal and child health service utilization across Kogi State. Significant improvements were observed in childhood immunization, Vitamin A supplementation, antenatal care attendance, skilled birth attendance, postnatal care utilization, and facility-based deliveries.

Second, despite these improvements, considerable heterogeneity existed across Local Government Areas, wards, and primary healthcare facilities. Administrative coverage concealed clusters of underserved communities characterized by poor geographical accessibility, inadequate community mobilization, weak health systems, and health workforce shortages.

Third, Bayesian Additive Regression Trees demonstrated excellent predictive performance in identifying children, pregnant women, breastfeeding mothers, and health facilities at highest risk of remaining unreached after campaign implementation. Predictor importance analysis consistently identified outreach implementation, cold-chain functionality, supportive supervision, CBHWs activities, facility readiness, commodity availability, and accessibility as major determinants of programme performance.

Fourth, multilevel causal mediation analysis demonstrated that a considerable proportion of programme effectiveness occurred indirectly through implementation mechanisms rather than direct intervention effects alone. Community mobilization, supportive supervision, outreach implementation, health workforce capacity, commodity availability, and cold-chain functionality significantly mediated improvements in maternal and child health outcomes.

Fifth, Bayesian spatial epidemiology using the BYM2 model identified statistically significant geographical clusters of residual implementation gaps. Spatial dependence demonstrated that neighbouring wards frequently shared similar implementation characteristics, thereby validating the need for geographically targeted interventions.

Sixth, integration of predictive modeling and Bayesian spatial analysis enabled development of a composite Mop-up Priority Index capable of ranking wards and facilities according to predicted implementation need.

Finally, the hybrid analytical framework successfully transformed routine MNCHW programme data into operational intelligence suitable for evidence-based programme management.

CONCLUSION

The findings demonstrate that Integrated MNCHW remains an effective strategy for improving maternal, newborn, and child health service coverage. Nevertheless, conventional programme evaluation approaches are insufficient for identifying residual implementation gaps, understanding causal mechanisms, or guiding precision mop-up activities.

The study therefore concludes that translational epidemiology provides an effective scientific paradigm for bridging the gap between epidemiological evidence and programme implementation. By integrating systematic evidence synthesis, Bayesian machine learning, multilevel causal mediation analysis, and Bayesian spatial epidemiology, routine programme data can be transformed into actionable implementation intelligence that supports precision public health.

The application of Bayesian Additive Regression Trees substantially improved prediction of unreached beneficiaries, while multilevel mediation analysis identified the implementation mechanisms responsible for programme effectiveness. Similarly, BYM2 Bayesian disease mapping provided robust identification of geographical hotspots requiring targeted intervention.

The study therefore concludes that implementation science, when integrated with modern epidemiological analytics, significantly enhances programme monitoring, implementation fidelity, resource allocation, accountability, and health equity. Overall, the proposed Hybrid Translational Epidemiology Framework represents a significant methodological advancement for maternal and child health programme evaluation and offers a scalable model for strengthening primary healthcare systems in Nigeria and similar resource-constrained settings.

The following proposed recommendations are based on the findings;

Technical

1. Prioritize completion rather than first contact by use of Penta1–Penta3, measles and full-schedule dropout as core precision-immunization indicators rather than relying on aggregate coverage alone.

2. Target adolescent reproductive health explicitly by warranting an adolescent-responsive FP, sexuality education, community engagement and referral integration derived from the Kogi State 19.1% ever-pregnant estimate among adolescent girls that is sufficiently high.

3. Retain the Bayesian spatial targeting strategy. The hotspots identified should be used for intensified microplanning, but the posterior LGA estimates should be re-estimated using the validated underlying data before journal submission.

4. Strengthen maternal-service continuity through the use of the Kogi Staste strong ANC/SBA/PNC performance as a platform for integrated family planning, nutrition, immunization completion and adolescent health interventions.

5. Perform genuine external validation of BART/BYM2 through the use of the DHS which can be used to validate population-level epidemiological plausibility, but not model discrimination, causal mediation or LGA posterior risk. A separate held-out Kogi dataset, subsequent MNCHW round, or another Nigerian state should be used for true external validation.

Policy

6. Federal and State Ministries of Health should institutionalize translational epidemiology within routine MNCHW programme monitoring.

7. Bayesian spatial epidemiology should become part of routine programme planning for identifying underserved communities.

8. Routine health information systems should incorporate predictive analytics to support precision public health.

9. Implementation science indicators should complement conventional programme coverage indicators.

Programme

5. State Primary Health Care Development Agencies should adopt predictive risk stratification before planning mop-up activities.

6. Community mobilization strategies should be strengthened through expanded CBHWsimplementation.

7. Supportive supervision should prioritize poorly performing facilities identified by predictive models.

8. Cold-chain strengthening should remain a strategic priority.

9. Microplanning should incorporate GIS and Bayesian hotspot maps.

10. Routine programme dashboards should integrate predictive and spatial indicators.

Health Systems

11. Strengthen health workforce capacity through continuous implementation science training.

12. Improve interoperability between DHIS2, GIS platforms, and routine surveillance databases.

13. Expand electronic data quality assurance systems.

14. Increase investments in primary healthcare infrastructure.
15. Strengthen multisectoral collaboration involving local governments, communities, development partners, and civil society.

Research

16. Future studies should externally validate the BART prediction model using datasets from other Nigerian states.
17. Longitudinal implementation research should evaluate sustainability of precision mop-up strategies.
18. Future studies should integrate satellite-derived accessibility measures and climate variables.
19. Cost-effectiveness analyses should evaluate economic benefits of precision microplanning.
20. Artificial intelligence and deep learning approaches should be explored alongside Bayesian models.

Contribution to Knowledge

This study makes several important contributions to epidemiology, implementation science, and maternal and child health.

First, it proposes one of the first integrated Hybrid Translational Epidemiology Frameworks combining PRISMA-ScR, Bayesian Additive Regression Trees, multilevel causal mediation analysis, and BYM2 Bayesian spatial epidemiology for Integrated MNCHW evaluation.

Second, it demonstrates the operational application of Bayesian machine learning for predicting unreached beneficiaries during maternal and child health campaigns.

Third, it provides empirical evidence regarding the implementation pathways through which community mobilization, supportive supervision, outreach implementation, and health systems strengthening improve programme outcomes.

Fourth, it demonstrates practical integration of Bayesian disease mapping into routine programme microplanning.

Fifth, it introduces a novel Mop-up Priority Index capable of supporting precision public health planning.

Finally, it advances translational epidemiology by explicitly linking evidence synthesis, predictive analytics, causal inference, spatial epidemiology, and implementation science within a single operational framework.

Policy Implications

1. Routine monitoring systems should transition from descriptive reporting toward predictive implementation intelligence.
2. Resource allocation should prioritize areas identified through predictive risk stratification rather than relying solely on administrative coverage.
3. National MNCHW operational guidelines should incorporate Bayesian spatial epidemiology and predictive analytics.
4. The Basic Health Care Provision Fund (BHCPF) should support digital implementation intelligence systems that integrate routine surveillance, GIS, and machine learning.
5. The study further supports implementation of Nigeria's Health Sector Renewal Investment Initiative, Primary Health Care Revitalization Agenda, Immunization Agenda 2030, Universal Health Coverage, and the Sustainable Development Goals.

Strengths of the Study

The study is strengthened by the integration of four complementary advanced epidemiological methodologies, underpinned by sa strong implementation science foundation that facilitates the translation of routine programme data into actionable operational intelligence. The use of Bayesian hierarchical models appropriately accounts for uncertainty, while the application of precision public-health principles supports targeted and context-specific interventions. In addition, the study generates operationally relevant predictive and spatial decision-support tools and develops a scalable analytical framework with potential applicability across low- and middle-income countries.

Limitations of the Study

Routine programme data may contain reporting errors, missing observations, residual confounding, and spatial inaccuracies despite rigorous data-quality procedures and advanced causal and spatial modelling, while predictive models may require periodic recalibration as programme conditions evolve. Furthermore, because the study was conducted in Kogi State, generalizability to other settings should be interpreted cautiously and confirmed through external validation and replication studies.

Suggestions for Future Research

Future research should validate the Hybrid Translational Epidemiology Framework across multiple Nigerian states and other low- and middle-income country settings to assess its external validity and adaptability. Further studies should incorporate real-time geospatial surveillance and satellite-derived accessibility metrics, while exploring explainable artificial intelligence (XAI) alongside Bayesian machine-learning approaches to improve transparency, prediction, and decision-making. Research should also evaluate the implementation costs, cost-effectiveness, and return on investment of precision mop-up interventions and develop integrated national digital decision-support platforms linking DHIS2, GIS, electronic logistics management information systems, and community health information systems. Where contextually appropriate, future investigations should additionally examine the application of genomic and environmental epidemiology to strengthen precision public-health surveillance and intervention targeting.

This study has demonstrated that the future of maternal, newborn, and child health programme evaluation lies beyond conventional descriptive epidemiology. The integration of translational epidemiology, implementation science, Bayesian machine learning, causal inference, and spatial epidemiology provides a comprehensive and operationally relevant framework for improving programme effectiveness. By transforming routine MNCHW data into actionable implementation intelligence, the proposed Hybrid Translational Epidemiology Framework enables precision microplanning, targeted mop-up, equitable resource allocation, and adaptive programme management.

The framework offers a scalable, scientifically rigorous, and policy-relevant model that supports Nigeria's primary healthcare transformation agenda while contributing to the achievement of Universal Health Coverage, Immunization Agenda 2030, the Sustainable Development Goals, and broader global maternal and child health priorities. It provides a strong foundation for future research, policy development, and implementation practice aimed at reducing inequities and ensuring that no eligible mother or child is left behind.

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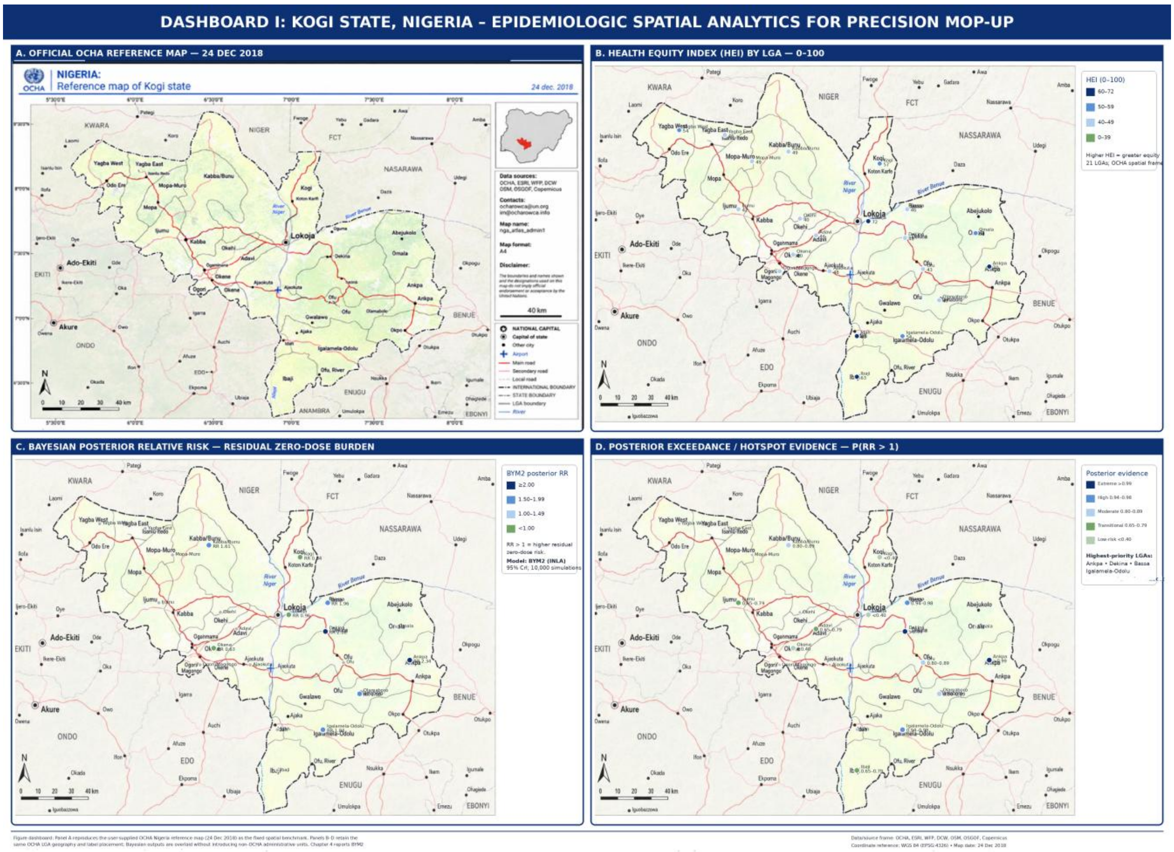
Appendix A



Appendix B