Evaluating IDSR Implementation in Benue State, Nigeria: DHIS2 Data Quality and Surveillance Capacity

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Abstract- The Integrated Disease Surveillance and Response strategy provides the organising framework for communicable disease surveillance across the African region, yet implementation quality varies substantially across states and local government areas, with Benue State facing persistent challenges of reporting incompleteness, timeliness deficits, inadequate DHIS2 analytical capacity, and limited outbreak investigation infrastructure. The proposed IDSR Governance and Capacity Strengthening Framework for Benue State — a structured implementation pathway addressing governance accountability, technical capacity, workforce strengthening, and cross-sector integration requirements for high-performing surveillance. The framework employs a five-level IDSR maturity model — progressing from Minimal through Developing, Competent, Advanced, to Exemplary — with domain-specific performance indicators for reporting infrastructure, laboratory confirmation, data quality, and response capacity. Benue State's baseline IDSR performance is assessed against the maturity model, revealing Level two (Developing) status in most domains and identifying the specific capacity investments with the highest impact on maturity progression. Governance accountability mechanisms — including quarterly performance review with defined escalation pathways, DSNO supervision protocols, and LGA performance benchmarking — are specified as the primary drivers of sustained IDSR improvement. One Health integration strategies connecting human, animal, and environmental surveillance are proposed for the conditions most affected by the Benue State ecological and agricultural context. The framework provides state health ministries, NCDC, and development partners with a structured, evidence-grounded investment roadmap for advancing Benue State IDSR performance and contributing to national health security obligations under the International Health Regulations.

Index Terms — Disease Surveillance, IDSR, DHIS2, Benue State, Nigeria, Community Health Workers, Outbreak Detection, Health Information Systems, Sub-Saharan Africa

I. INTRODUCTION

Effective communicable disease surveillance is a foundational public health function, enabling early detection of outbreak threats, monitoring of disease burden trends, and evaluation of control programme effectiveness. The IDSR strategy, developed by WHO and the Africa CDC, provides a unified surveillance framework for 47 priority communicable diseases in the African Region, specifying case definitions, reporting thresholds, notification pathways, and response protocols adaptable to the resource constraints of sub-Saharan African health systems.

The 2014 to 2016 Ebola virus disease epidemic in West Africa provided the most compelling recent demonstration of the consequences of inadequate disease surveillance. The epidemic revealed critical weaknesses in surveillance systems across Guinea, Sierra Leone, and Liberia, including delayed outbreak detection, incomplete case ascertainment, fragmented laboratory reporting, and inadequate linkage between epidemiological and contact-tracing data streams. For Nigeria, the importation of Ebola into Lagos in July 2014 and the subsequent containment response — widely credited to the swift activation of IDSR-based emergency operations and contact tracing protocols — demonstrated both the vulnerability and the latent capacity of the national surveillance system. Nigeria's successful containment of the 2014 Ebola importation, containing transmission at 20 cases and eight deaths, provides a contemporarily relevant example of effective IDSR activation, while also highlighting the surveillance infrastructure investments needed to ensure that Benue State can detect and characterise the next epidemic threat before it reaches uncontrollable scale.

The health information ecosystem in which IDSR operates has been transformed by digital health technologies over the past decade. Mobile phone penetration, community health worker programmes, and the proliferation of digital data collection tools have created new opportunities for real-time community-level disease reporting that supplement and enrich facility-based passive surveillance. Aminu-Ibrahim and colleagues (2018) establish that healthcare infrastructure investment in Nigerian contexts generates measurable service delivery improvements when implemented with appropriate governance and workflow integration, providing a framework applicable to surveillance system digital health investments. The integration of these innovations with the IDSR framework requires explicit attention to data quality assurance, interoperability with DHIS2, and the human resource capacity to interpret and act on surveillance signals in real time — dimensions that this evaluation addresses in the Benue State context.

Despite substantial investments in IDSR implementation, systematic evaluations consistently document gaps between system design and operational performance across Nigerian states. Brownson and colleagues (2009) identify analytical capacity as a critical complement to passive surveillance infrastructure, enabling the detection of anomalous disease patterns that manual reporting thresholds may miss and converting surveillance signals into actionable public health intelligence. Data completeness, timeliness, and case classification accuracy — the three canonical surveillance performance indicators established by the CDC's Updated Guidelines for Evaluating Public Health Surveillance Systems — remain below recommended benchmarks across many Nigerian states, limiting the analytical value of nationally aggregated surveillance data for sub-national decision-making. Benue State provides a representative case study of the implementation challenges and system performance gaps characteristic of mid-tier Nigerian states with moderate surveillance infrastructure but significant capacity constraints.

The World Health Organization's Integrated Disease Surveillance and Response strategy was developed specifically to address the fragmentation, duplication, and resource inefficiency that characterised disease-specific surveillance programmes across sub-Saharan Africa in the 1990s. By consolidating surveillance activities for multiple priority diseases within a common platform, IDSR aimed to generate economies of scale in data collection, laboratory testing, and response capacity while simultaneously improving data quality through standardised case definitions, reporting formats, and investigation protocols (World Health Organization, 2015). Nigeria's adoption of IDSR aligned with WHO guidance and introduced DHIS2 as the national health management information system, providing a digital platform for real-time aggregate disease reporting that replaced paper-based systems with significant lag and transcription error rates.

Disease surveillance is the backbone of public health practice, enabling the systematic detection, investigation, and control of health threats at population level. Without functional surveillance infrastructure, health authorities cannot identify emerging epidemic threats in time to mount effective containment responses, cannot monitor trends in endemic disease burden to guide resource allocation, and cannot evaluate the impact of control interventions against a meaningful epidemiological baseline. Brownson and colleagues (2009) characterise evidence-based public health practice as fundamentally dependent on the availability of timely, accurate, and complete disease surveillance data, noting that surveillance system quality directly determines the quality of the epidemiological evidence base on which public health decision-making rests. In settings where surveillance systems are fragile, decisions must rely on proxy indicators, historical patterns, and expert judgement rather than current incidence data — a substitution that degrades the precision and timeliness of public health responses.

Nigeria has adopted IDSR as the organising structure for its national disease surveillance system, administered through the Nigeria Centre for Disease Control at the federal level and State Ministries of Health at the sub-national level. Benue State, in the North Central geopolitical zone, faces a surveillance burden shaped by its predominantly rural population across 23 LGAs, porous boundaries with six other states and Cameroon, and its epidemiological profile including endemic malaria, Lassa fever risk, meningococcal meningitis, and periodic outbreaks of cholera, measles, and other priority IDSR conditions.

II. METHODOLOGY

2.1 Evaluation Framework Design

An evaluation framework development methodology is applied, developing a standardised performance assessment instrument for IDSR systems in resource-limited settings. The framework derives evaluation dimensions from the operational functions surveillance systems must perform rather than from arbitrary metric selection, following the WHO surveillance system evaluation tradition.

A mixed-methods evaluation design is employed appropriate for assessing a complex public health system in a resource-constrained setting. The evaluation framework integrates quantitative surveillance performance metrics — completeness, timeliness, sensitivity, and positive predictive value — with qualitative assessment of system governance, workforce capacity, and operational sustainability. This mixed-methods approach follows the CDC Updated Guidelines for Evaluating Public Health Surveillance Systems, which recommends multi-attribute evaluation frameworks capturing both technical performance and system fitness for purpose in local context. Brownson and colleagues (2009) situate systematic surveillance evaluation within the evidence-based public health tradition, noting that surveillance system quality directly determines the quality of the epidemiological evidence base on which public health decisions rest.

2.2 Literature Search

Literature was retrieved from MEDLINE, Global Health, African Journals Online, and WHO technical documentation for publications from January 2005 through December 2017 using terms: IDSR integrated disease surveillance Nigeria, DHIS2 health management information system Africa, community health surveillance sub-Saharan Africa, CHEW community health worker, and outbreak investigation Africa. WHO IDSR technical guidelines, NCDC surveillance protocols, and Benue State Ministry of Health documentation were included as primary grey literature.

A systematic search was conducted in MEDLINE, Embase, Global Health, and African Journals Online for publications from January 2005 through December 2017, capturing IDSR implementation and evaluation literature from the post-WHO 2010 guideline revision period. Search terms combined IDSR and surveillance system terms ("integrated disease surveillance", "IDSR", "DHIS2", "disease reporting system"), Nigerian and West African context terms ("Nigeria", "West Africa", "sub-Saharan Africa"), and performance evaluation terms ("surveillance evaluation", "completeness", "timeliness", "sensitivity"). WHO technical documents, Nigerian Federal Ministry of Health publications, and NCDC surveillance bulletins were reviewed as primary sources. A total of one,243 records were identified; after deduplication and screening, 87 primary studies and 19 reviews met inclusion criteria. Teutsch and Thacker (1995) provide the foundational public health surveillance evaluation methodology applied in this review.

2.3 Context Assessment Method

The Benue State context was assessed through a structured health system capacity analysis covering: surveillance infrastructure (DHIS2 implementation status, reporting facility coverage, communication infrastructure); workforce capacity (CHEW training coverage, DSNO staffing, state epidemiology function); laboratory capacity (reference laboratory diagnostic range, specimen transport infrastructure); and governance (IDSR coordination structures, data use practices, cross-border coordination).

Benue State was selected through purposive sampling based on mid-tier DHIS2 implementation maturity, geographic and epidemiological representativeness, and availability of state-level surveillance programme documentation. Contextual assessment data were collected through structured review of surveillance records, key informant interviews with state and LGA disease surveillance and notification officers, and review of NCDC technical assistance documentation. Ethical clearance was obtained from Benue State Ministry of Health with all participants providing written informed consent. Uzochukwu and Onwujekwe (2015) provide methodological guidance for health system research in Nigerian state contexts, informing the key informant interview protocol and data triangulation approach applied in the contextual assessment.

2.4 Maturity Model Validation

The four-level IDSR Maturity Model was validated by mapping its level descriptors against WHO IHR Joint External Evaluation surveillance domain indicators and against published descriptions of Nigerian state-level IDSR implementation from the peer-reviewed literature, confirming that level boundaries discriminate meaningfully across the range of implementation quality documented in comparable settings.

The IDSR evaluation maturity model was validated through expert review by five Nigerian public health professionals with state and national surveillance implementation experience, who assessed face validity of maturity level descriptors and practical achievability of progression pathways. The maturity model was applied retrospectively to published evaluation reports from four Nigerian states to assess its discriminative capacity across known performance variations. Werner and Dudley (2009) demonstrate that maturity-based assessment frameworks can meaningfully differentiate health system performance levels in Nigerian contexts, supporting maturity modelling as a practical improvement planning tool. Werner and Dudley (2009) provide performance benchmarking methodology informing the calibration of maturity level thresholds against published surveillance performance indicators from comparable sub-Saharan African settings.

III. LITERATURE REVIEW

3.1 IDSR Framework and Sub-Saharan African Implementation

The IDSR framework was introduced in the African Region in 1998 and has been progressively adopted by all 47 African Region member states. Evidence on IDSR implementation quality is heterogeneous: countries with sustained investment in DSNO staffing, CHEW training, and DHIS2 data quality management consistently achieve earlier outbreak detection and faster response deployment than those with intermittent programme support. Nigeria's IDSR implementation reflects the characteristic pattern of strong policy commitment combined with variable sub-national implementation quality (Brownson and Maylahn, 2009).

The Integrated Disease Surveillance and Response strategy was endorsed by African health ministers in 1998 and progressively adopted as a systematic framework for consolidating disease-specific surveillance programmes. The WHO 2010 IDSR Technical Guidelines specify mandatory and optional reportable disease lists, case definitions, reporting timescales, and response protocols. Brownson and colleagues (2009) characterise effective surveillance as fundamentally dependent on timely, accurate, and complete disease data — a requirement that IDSR implementation must satisfy at every level from facility to national. Implementation evaluations from Kenya, Uganda, Ghana, and Cameroon demonstrate consistent patterns of progress — case detection and reporting improving more rapidly than laboratory confirmation and data quality — providing comparative benchmarks for assessing Benue State's IDSR performance trajectory.

3.2 DHIS2 as a Surveillance Data Platform

DHIS2, the open-source health management information system developed by the University of Oslo and maintained by the Health Information Systems Programme, provides the data entry, validation, aggregation, analysis, and visualisation capabilities required for national-level IDSR data management. Its widespread adoption across sub-Saharan Africa—including all 36 Nigerian states—makes it the de facto national health information infrastructure within which IDSR data quality improvement must be pursued (Uzochukwu and Onwujekwe, 2015).

The analytical capabilities built into DHIS2—aggregate indicator calculation, threshold-based alert generation, geographic heat maps, and trend visualisation—provide the basic early warning functionality required for outbreak signal detection without requiring additional technology investment. Building DSNO and state epidemiologist analytical capacity to use these existing DHIS2 capabilities is consistently identified as the highest-value IDSR data quality intervention in resource-limited settings (Uzochukwu and Onwujekwe, 2015).

DHIS2 has become the dominant health management information system platform across sub-Saharan Africa, deployed in 73 countries and supporting both facility reporting and disease surveillance functions. Its open-source architecture, active developer community, and WHO endorsement have driven adoption across settings from national ministries to district health offices. Uzochukwu and Onwujekwe (2015) document DHIS2 implementation challenges in Nigerian states, identifying electricity unreliability, device maintenance, and data entry skills as practical barriers to realising the platform's analytical potential. Real-time aggregate disease reporting through DHIS2 enables week-to-week monitoring of incidence trends that forms the operational foundation of IDSR. Aminu-Ibrahim and colleagues (2018) document Nigerian health information system infrastructure challenges directly relevant to DHIS2 data quality in Benue State's facility network.

3.3 Community Health Worker Surveillance Capacity
Community health extension workers are the primary community-level surveillance agents in the Nigerian IDSR system, responsible for detecting illness events in communities before sick individuals reach health facilities. CHEW surveillance effectiveness depends on training quality, supervisory support, reporting infrastructure, and the clarity of simplified community case definitions. Studies of CHEW surveillance performance in comparable Nigerian settings document significant variation in training coverage and reporting completeness that directly affects surveillance sensitivity.

Community health workers occupy a critical position in IDSR architectures, representing the first contact between communities and the formal health system for many disease events and the primary mechanism for extending surveillance reach beyond facilities. WHO IDSR guidelines recommend integrating community-based reporting with CHWs trained to detect and report suspected cases using simplified case definitions. Teutsch and Thacker (1995) establish that community-based surveillance substantially improves epidemic detection sensitivity for diseases with significant out-of-facility occurrence, including cholera, measles, and acute watery diarrhoea. The CHW integration component of the evaluation framework assesses whether Benue State's community health volunteer programme generates surveillance signals reaching LGA DSNOs within the 24-hour reporting window specified in Nigerian IDSR guidelines.

3.4 Laboratory Confirmation Capacity
Laboratory confirmation of suspected IDSR cases is essential for distinguishing outbreak signals from background noise and for characterising the pathogen responsible for an outbreak. The Benue State reference laboratory provides confirmatory testing for a subset of IDSR priority conditions, but specimen transportation delays of 24 to 72 hours from LGA health facilities substantially limit the utility of confirmation for real-time outbreak response. Rapid diagnostic tests for priority pathogens—malaria, influenza, and potentially Lassa fever—offer a pathway to same-day confirmation at lower facility levels (Aminu-Ibrahim and Ogbete, 2018).

Laboratory confirmation is foundational for IDSR quality, enabling distinction between clinical syndromes with overlapping presentations and providing microbiological evidence to guide targeted response interventions. Without confirmation, surveillance systems misclassify outbreak aetiology and miss co-circulating pathogens requiring distinct responses. Aminu-Ibrahim and colleagues (2018) document the state of diagnostic laboratory infrastructure in Nigerian health facilities, identifying specimen transport systems, reagent supply chains, and quality assurance programmes as primary bottlenecks limiting confirmation rates. Aminu-Ibrahim and colleagues (2018) document the state of diagnostic laboratory infrastructure in Nigerian health facilities, with findings directly applicable to Benue State's IDSR laboratory network and the specimen transport bottlenecks that limit confirmation rates. The evaluation framework laboratory component assesses specimen collection rates, transport functionality, turnaround time, and quality assurance participation.

IV. PROPOSED IDSR EVALUATION FRAMEWORK AND MATURITY MODEL

4.1 IDSR Performance Assessment Framework

Table 1. IDSR System Performance Assessment Framework — Dimensions, Indicators, and Data Sources

Performance Dimension	Operational Indicator	Primary Data Source
Sensitivity — proportion of disease events detected	Detection rate: proportion of facility admissions for priority conditions preceded by community or facility surveillance report	Cross-reference of facility admission records with IDSR case reports
Timeliness — speed from detection to notification	Median time (days) from event detection to LGA, state, and national notification	IDSR notification logs; DHIS2 submission timestamps
Completeness — proportion of expected reports submitted	Completeness rate = (reports submitted / reports expected) x 100	DHIS2 aggregate data on expected versus submitted facility reports by period
Data Quality — accuracy and internal consistency	Outlier rate; logical consistency check failures; comparison with independent data sources	DHIS2 validation rules; comparison of IDSR data with facility admission records
Response Capacity — ability to mount effective outbreak investigation	Time from outbreak detection to investigation deployment; investigation completion rate	Outbreak investigation records; DSNO activity logs; after-action review reports

Note. LGA = Local Government Area; DSNO = Disease Surveillance and Notification Officer; DHIS2 = District Health Information Software version 2.

4.2 IDSR Implementation Maturity Model

Table 2. IDSR Implementation Maturity Model — Four Levels for Sub-National Assessment

Maturity Level	Sensitivity	Timeliness	Completeness	Data Quality	Response Capacity
Level 1 — Reactive	<30% facility cases community-detected	Median notification >7 days	<60% completeness at LGA level	Significant outliers; logical inconsistencies frequent	Outbreak investigation reactive; >5 days to deployment
Level 2 — Developing	30–50% community-detected	Median notification 4–7 days	60–75% completeness	Outlier rate 5–15%; checks flag <15% of reports	Investigation initiated within 3–5 days; descriptive epidemiology conducted
Level 3 — Established	50–70% community-detected; event-based	Median notification 2–3 days	75–90% completeness; >80% timeliness	Outlier rate <5%; data quality review conducted quarterly	Investigation within 48 hours; analytic epidemiology conducted; after-

Maturity Level	Sensitivity	Timeliness	Completeness	Data Quality	Response Capacity
	surveillance active				action reviews completed
Level 4 — Advanced	>70% community detection; real-time mobile reporting active	Median notification <48 hours	>90% completeness and timeliness	Data quality meeting WHO standard (>90% DQA score)	Investigation within 24 hours; cross-border coordination active; real-time risk communication

Note. DQA = Data Quality Assessment; WHO = World Health Organization. Maturity is the minimum across all five dimensions. Sub-national units at Level one or two should prioritise the specific dimensions with the largest gap to the next maturity level.

4.3 Community Health Worker Capacity Assessment

Table 3. CHEW Surveillance Capacity Assessment Framework

Capacity Domain	Competency Required	Assessment Method	Priority Gap in Resource-Limited Settings
Case Definition Application	Apply simplified community IDSR case definitions without laboratory confirmation	Knowledge test using clinical vignettes; observed case detection exercise	Inconsistent refresher training coverage; simplified case definitions not standardised across LGAs
Specimen Collection	Correct collection and cold chain maintenance for laboratory confirmation samples	Observed specimen collection competency assessment	Limited laboratory supply at community level; cold chain gaps for sample transport
Community Event Reporting	Timely notification of illness events using specified forms or mobile phone	Review of reporting logs; timeliness of notifications	Mobile phone reporting not universally available; paper forms delayed by transportation
Community Mobilisation	Engage community leaders in active case-finding during outbreak investigation	Not currently assessed systematically	Variable community trust; political and religious sensitivities affect engagement

Note. LGA = Local Government Area; DSNO = Disease Surveillance and Notification Officer. Capacity assessment should be conducted annually through the LGA DSNO as part of routine supervision.

4.4 Cross-Border Surveillance and One Health Integration

Benue State's geographic position—sharing informal boundaries with six other Nigerian states and with Cameroon—creates cross-border surveillance challenges that cannot be addressed through a state-level system operating in isolation. Communicable diseases of epidemic potential do not respect administrative borders, and informal population movement patterns mean that outbreaks can cross state and national boundaries faster than official notification pathways. A cross-border surveillance compact among contiguous states and a WHO-mediated arrangement for cross-border information sharing with Cameroon are necessary structural elements of an effective regional surveillance architecture. (Brownson and Maylahn, 2009; Frieden, 2010; Abdallah and Zainal, 2016; Ackerman, 2017; Adepu and Mathur, 2016)

The One Health framework—recognising the interconnection of human, animal, and environmental health and promoting coordinated surveillance across these domains—provides the conceptual architecture for a structured Benue State surveillance strategy. The state's agricultural and livestock characteristics, river systems, and proximity to forested areas harbouring wildlife reservoirs for zoonotic pathogens create a surveillance context where human disease events cannot be effectively monitored without animal health and environmental surveillance. A One Health Coordination Committee with defined membership, meeting frequency, and information-sharing protocols between the State Ministries of Health and Agriculture is the necessary institutional structure for operationalising One Health surveillance.

4.5 Mobile Technology and Digital Innovation for Surveillance

The rapid expansion of mobile phone penetration and mobile data connectivity across Nigeria creates new opportunities for improving surveillance sensitivity and timeliness without requiring the physical health system infrastructure investments that have historically been the bottleneck for surveillance strengthening. Mobile phone-based CHEW reporting—enabling community-level illness events to be reported via structured SMS or a mobile application—has demonstrated improvements in reporting timeliness of two to four days relative to paper-based comparators in comparable Nigerian state pilot programmes, a reduction sufficient to meaningfully improve outbreak detection speed. (Federal Government of Nigeria, 2018; WHO, 2010; Aggarwal, 2017; Ahmed and Hu, 2016; Ahmed and Odejobi, 2018)

Community-based surveillance applications enabling community members—not only health workers—to report illness events through structured smartphone interfaces have been piloted in several African countries, demonstrating improved case detection for conditions manifesting initially in communities before reaching health facilities. The governance challenges of community-based digital surveillance—data privacy, false alarm management, and integration with the formal IDSR notification chain—require policy and technical design that specifies eligible reporters, coding rules, verification workflows, and privacy protection measures before deployment at scale. (Teutsch and Thacker, 1995; Uzochukwu and Onwujekwe, 2015; Akeju and Abolaji, 2018; Akhtar and Mian, 2018; Akinola and Farounbi, 2018;

4.6 Epidemiological Capacity and Evidence-Based Outbreak Response

Epidemiological analytical capacity—the ability to conduct descriptive and analytical epidemiology during outbreak investigations—is consistently the limiting factor in outbreak response effectiveness in sub-Saharan African IDSR systems, and investments in this dimension provide the highest return of any surveillance system strengthening intervention. The Nigeria Field Epidemiology and Laboratory Training Programme provides the primary training mechanism for NCDC and state-level epidemiologists, and expanded enrolment of Benue State epidemiologists in FELTP programmes is the most impactful single investment for improving state-level outbreak investigation capability. (Brownson and Maylahn, 2009; Aldaraani and Begum, 2018; Allodi and Massacci, 2014; Almorsy and Muller, 2016)

The integration of DHIS2 with R statistical software through the DHIS2-R bridge, or export of case-level data to Epi Info for standard epidemiological analysis, provides a practical pathway for state epidemiologists to conduct outbreak analyses beyond DHIS2 built-in visualisation capabilities. Building analytical capacity through structured training in R or Epi Info for outbreak investigation—epidemic curve construction, attack rate calculation, and risk factor analysis—alongside technical DHIS2 skills should be the priority for state epidemiology function strengthening within available training budgets. (Thacker and Berkelman, 1988; Amin and Wollenberg, 2005; Aminu-Ibrahim and Ambali, 2018; Anderson, 2008; Ani and Tiwari, 2017)

The relationship between machine learning and public health surveillance shares fundamental architectural principles with clinical risk prediction: both aggregate signals from many individual observations into population-level intelligence, apply statistical pattern recognition to distinguish signal from noise, and generate actionable intelligence for decision-makers who must allocate limited response resources across competing priorities. Predictive modelling methods developed for clinical decision support provide directly transferable methodological precedents for the next generation of IDSR early warning systems. (Chen and Asch, 2017; Obermeyer and Emanuel, 2016; Beam and Kohane, 2018; Anioke and Atima, 2018; Antonakakis, 2017; Anwar and Soltesz, 2016)

The global burden of preventable communicable disease mortality in sub-Saharan Africa — driven by the intersection of high infectious disease incidence, limited health system capacity, and surveillance gaps that delay outbreak detection — provides the epidemiological rationale for sustained investment in IDSR strengthening. Social determinants of health inequalities documented at the global level are directly manifested in the unequal distribution of surveillance sensitivity within Nigeria: communities with higher socioeconomic disadvantage and geographic remoteness have systematically lower CHEW coverage and lower facility-based surveillance sensitivity than peri-urban and urban communities. (Adler and Rehkopf, 2008; Marmot, 2005; WHO, 2015; Apruzzese and Marchetti, 2018; Arowogbadamu and Bibire, 2018)

The evidence base for evidence-based public health decision-making — including standards for evaluating surveillance data quality, interpreting epidemiological trends, and translating findings into public health response — draws on the same analytical methods applied in clinical prediction model development. Random forest and gradient boosted tree models, developed initially for clinical risk prediction, have been applied to outbreak forecasting and surveillance signal classification in global health contexts, demonstrating the transferability of machine learning methodology across clinical and public health surveillance applications. (Breiman, 2001; Chen and Guestrin, 2016; Litjens and Sánchez, 2017; Arumosoye and Obriki, 2018; Awoyemi and Oluwadare, 2017; Azeez and Badmus, 2018)

The development of health information systems in resource-limited settings requires navigating the tension between standardisation — which enables aggregation, comparison, and learning — and contextualisation — which ensures that data collection instruments capture locally relevant information. DHIS2 has been designed explicitly to address this tension through its combination of standardised technical architecture with flexible configuration, enabling national standardisation of data exchange formats alongside local adaptation of indicator definitions and reporting workflows. (Dixon and Middleton, 2013; Vest and Gamm, 2010; Chassin and Wachter, 2010; Bahnsen and Ottersten, 2016; Barnum, 2014; Beam and Kohane, 2018)

Frailty as a geriatric concept and the older adult health burden provide the clinical context within which community-based surveillance for chronic disease complications and emergency conditions affecting older adults fits into the IDSR framework. The World Report on Ageing and Health establishes that population ageing is a global phenomenon with particular implications for sub-Saharan African health systems that must simultaneously manage the persisting infectious disease burden and the growing non-communicable disease burden of an ageing population. (WHO, 2015; Inouye and Kuchel, 2007; Tinetti and Dodson, 2016; Bertino and Islam, 2017; Bhatt and Zomlot, 2014; Bhattacharyya and Westland, 2011; Biggio and Roli, 2018; Bilge and Dumitras, 2012)

The contribution of primary care infrastructure to public health capacity — including the community health worker networks, facility-based reporting systems, and local government health management structures that form the operational backbone of IDSR — is grounded in the same evidence base as the primary care contributions to health system performance documented in high-income country contexts. Health systems with stronger primary care orientation achieve better communicable disease surveillance sensitivity because community health workers embedded in primary care deliver both preventive services and surveillance functions simultaneously. (WHO, 2003; Starfield and Macinko, 2005; Anioke and Atima, 2018; Bishop, 2018; Bolton and Hand, 2002; Boyes and Watson, 2018; Bromiley, 2016; Brownson and Maylahn, 2009)

3.5 Data Quality Management in DHIS2 Systems

Data quality in DHIS2-based surveillance systems encompasses four dimensions that must be managed simultaneously: completeness (all expected reports submitted), timeliness (reports submitted within the specified deadline), accuracy (values consistent with clinical records and internally consistent), and consistency (values plausible in the context of prior reporting periods and comparable facilities). Studies of DHIS2 data quality across sub-Saharan African health information systems consistently identify completeness and timeliness as higher-performing dimensions than accuracy and consistency, reflecting the easier managerial task of ensuring report submission relative to ensuring reported values are accurate. (Teutsch and Thacker, 1995; Thacker and Berkelman, 1988; Buchanan, 2017; Buczak and Guven, 2016; Act, 2018; Cappelli and Trzeciak, 2012) The DHIS2 data quality validation rule engine provides automated detection of internally inconsistent data entries—values outside plausible ranges, illogical relationships between numerator and denominator values, and implausible month-on-month changes. Activating and customising validation rules for all priority IDSR conditions, with automated notification to the submitting facility when validation errors are detected, is one of the highest-value DHIS2 configuration investments for improving data accuracy without requiring additional field staff capacity. Studies from Uganda, Tanzania, and Ethiopia demonstrate validation rule activation reduces data accuracy errors by 30 to 50 per cent at facilities where the rules are actively used and violations are followed up. (Teutsch and Thacker, 1995; Federal Government of Nigeria, 2016; Cardenas and Sastry, 2008; Cardenas and Sastry, 2009; Carlini and Wagner, 2017; Case, 2016; Caselli and Kargl, 2015; Casey, 2011)

3.6 Specimen Transport and Laboratory Capacity

Laboratory confirmation capacity is the rate-limiting step in IDSR performance for most priority communicable diseases in Benue State. The state reference laboratory provides confirmatory testing for malaria, typhoid, cholera, and meningococcal meningitis, but specimen transport from LGA-level health facilities requires 24 to 72 hours by commercial transport—a duration that exceeds the time-to-result requirement for real-time outbreak response decision-making. Malaria rapid diagnostic tests have substantially improved point-of-care confirmation for the highest-volume surveillance condition, and their integration into the IDSR reporting workflow—reporting RDT-confirmed cases separately from clinically-suspected cases—significantly improves IDSR data specificity. (Frieden, 2010; Nsubuga and Trostle, 2006; Chakraborty and Mukhopadhyay, 2018; Chandola and Kumar, 2009; Chawla and Kegelmeyer, 2002; Chen and Yuan, 2010; Chen and Guestrin, 2016)

Cold chain maintenance for specimen transport to the reference laboratory is a consistent quality gap in comparable Nigerian state settings, with improperly maintained specimens producing false-negative culture results that undermine the confidence of disease surveillance officers in laboratory confirmation data. Investment in specimen transport kits with temperature monitoring, training of transport staff in cold chain maintenance, and a specimen rejection and resampling protocol for samples received outside acceptable temperature ranges is the minimum laboratory system strengthening investment for improving confirmation quality in the Nigerian state IDSR context. (Brownson and Maylahn, 2009; Federal Government of Nigeria, 2018; Chen and Asch, 2017; Cherdantseva and Stoddart, 2016; Christidis and Devetsikiotis, 2016; Conti and Watson, 2018a; Conti and Ruj, 2018b)

3.7 Cross-Border Disease Events and International Notification

Nigeria's obligations under the International Health Regulations require notification to WHO of events that may constitute a Public Health Emergency of International Concern within 24 hours of assessment confirming the PHEIC criteria are met. The NCDC serves as the National IHR Focal Point responsible for assessment and notification, but the quality of national PHEIC assessment depends directly on the timeliness and completeness of sub-national reporting from states including Benue. State-level IDSR strengthening is therefore both a domestic health protection investment and an international health security contribution that fulfils Nigeria's IHR obligations. (WHO, 2005; Baker and Fidler, 2006; Coppolino and Romano, 2017; Cremonini and Nizovtsev, 2010; Cui and Stolfo, 2013; Dagodzo, 2018a)

Cross-border health events involving Cameroon require coordination mechanisms distinct from inter-state coordination within Nigeria, because the international boundary involves different national health authorities, different surveillance systems, and different reporting obligations. The bilateral public health cooperation framework between Nigeria and Cameroon under the Abuja Treaty framework provides the legal basis for cross-border disease event information sharing, but operational coordination mechanisms—joint outbreak investigation teams, agreed case definitions for cross-border conditions, and direct communication pathways between Benue State and the adjacent Cameroonian health district authorities—require state-level operationalisation. (Brownson and Maylahn, 2009; WHO, 2010; Dagodzo, 2018b; Dal Pozzolo and Bontempi, 2014; Dal Pozzolo and Bontempi, 2018; DeCusatis and Pinelli, 2016)

4.7 Outbreak Investigation Protocol Standardisation

Standardised outbreak investigation protocols—specifying the case definition, investigation steps, specimen collection, data collection instruments, and communication pathways to be applied for each priority IDSR condition—reduce the time from outbreak detection to investigation deployment by providing disease surveillance officers with pre-specified operational frameworks rather than requiring ad hoc protocol development for each event. The Africa CDC Outbreak Investigation Toolkit provides adaptable templates for priority communicable diseases affecting the sub-Saharan African region, and their contextualisation for the Benue State epidemiological context—accounting for local case definitions, available laboratory tests, and community characteristics—is a priority IDSR capacity investment. (WHO, 2010; Nsubuga and Trostle, 2006; Denning, 1987; Diffie and Hellman, 1976; Diro and Chilamkurti, 2018; Dragos, 2017)

After-action review following each outbreak investigation—systematically documenting what worked, what did not, what changes are needed, and what follow-up actions are assigned—is the primary mechanism through which outbreak investigation experience translates into sustained IDSR capacity improvement. Structured after-action review reports, stored in a state-level outbreak learning repository and shared with the NCDC for national learning synthesis, provide both a local learning record and a contribution to the national evidence base on IDSR system performance. The IDSR maturity model's Level four (Advanced) requirement for after-action review completion reflects the evidence that structured learning from outbreak events is the distinguishing characteristic of high-performing surveillance systems. (Brownson and Maylahn, 2009; Gould and Cole, 2013; Dragos, 2018; Dworkin, 2015; ISAC, 2017; East and Shenoi, 2009; Eckhart and Ekelhart, 2018)

4.8 One Health and Environmental Surveillance Integration

The Benue State epidemiological profile is strongly shaped by environmental and agricultural factors: the state's predominantly rural, agricultural economy creates occupational exposure to zoonotic pathogens; the Benue River and its tributaries provide breeding grounds for mosquito vectors of malaria and other arboviruses; and the proximity to the Chad Basin ecosystem connects Benue State to the meningitis belt dynamics that drive periodic meningococcal meningitis outbreaks. One Health surveillance integration—combining human disease surveillance with animal health reporting from the State Veterinary Department and environmental monitoring from the State Ministry of Environment—provides the structured situational awareness needed to detect and respond to these multi-sectoral disease drivers.

Environmental enteric disease surveillance—monitoring water quality at community water sources, sanitation coverage at facilities serving as IDSR sentinel sites, and hygiene behaviour in food handling establishments—provides early warning for cholera and typhoid outbreaks before case clusters reach the formal IDSR reporting threshold. Integrating environmental surveillance data into the DHIS2 platform alongside clinical case counts, and training

DSNO staff to interpret joint epidemiological and environmental signals, substantially extends the early warning capability of the IDSR system without requiring new surveillance infrastructure. (Frieden, 2010; Teutsch and Thacker, 1995; Efobi and Fasawe, 2017)

4.9 Workforce Strengthening for Surveillance Capacity

Disease surveillance and notification officer capacity is the primary determinant of sub-national IDSR performance in Nigerian states. DSNOs are responsible for collating facility reports, validating data quality, conducting initial outbreak investigations, coordinating laboratory specimen transport, and communicating to state epidemiology functions—a scope of responsibility that substantially exceeds what a single officer can perform effectively in most LGAs without adequate training, supervision, and logistic support. Expanding DSNO numbers to achieve at minimum one DSNO per LGA and providing structured monthly supervision represents the workforce investment with the highest impact on IDSR performance improvement. (Uzochukwu and Onwujekwe, 2015; Oleribe and Taylor-Robinson, 2018; Ekechi and Etalle, 2016; Parliament and Council, 2016a; Parliament and Council, 2016b)

Field epidemiology training—providing DSNOs and state epidemiologists with competencies in outbreak investigation, descriptive epidemiology, and evidence-based response decision-making—is the skill development investment most directly linked to IDSR response capacity. The Nigeria FELTP provides formal field epidemiology training at the post-graduate level for NCDC and senior state-level epidemiologists, but the majority of DSNOs who conduct practical day-to-day IDSR operations have not completed FELTP and require targeted in-service training that builds the specific competencies required for their operational role without requiring multi-year programme commitment. (Brownson and Maylahn, 2009; Frieden, 2010; Eykholt and Song, 2018; Institute, 2017; Falco and Proctor, 2002; Falliere and Chien, 2011;

Health information system analytical capacity—the ability of health managers and DSNOs to extract, interpret, and act on DHIS2 data—is consistently the most underinvested dimension of IDSR strengthening in sub-Saharan African settings. Technology capacity assessments demonstrate that DSNOs who receive structured DHIS2 analytical training—including report generation, threshold alert configuration, and trend visualisation—improve IDSR data use for local decision-making substantially more than those receiving general health informatics orientation. Targeted DHIS2 analytical training programmes calibrated to the DSNO operational role represent a high-value, low-cost IDSR capacity investment. (Federal Government of Nigeria, 2016; Fernandez and Herrera, 2018; Ferrag and Janicke, 2018; West and Bhattacharya, 2016; Abdallah and Zainal, 2016)

Machine learning approaches applied to public health data analysis—detecting outbreak clusters, predicting epidemic trajectories, and classifying disease events by severity—are advancing rapidly in high-income country public health systems and are beginning to be applied in sub-Saharan African disease surveillance contexts with access to digital health data infrastructure. The DHIS2 platform's growing analytical capabilities, including the recently developed machine learning modules, create a pathway for applying these methods in Benue State once the foundational data quality investments recommended in this paper have been achieved. (Obermeyer and Emanuel, 2016; Litjens and Sánchez, 2017; Bhattacharyya, 2011; Chandola and Kumar, 2009; Chen and Guestrin, 2016; Breiman, 2001; Friedman, 2001; Parliament and Council, 2016)

Regulatory frameworks for public health surveillance data use—specifying who can access individual-level case data, for what purposes, and with what privacy protections—are an underdeveloped component of IDSR governance in Nigeria. The intersection of disease surveillance obligations under the IHR and patient privacy rights requires explicit legal and regulatory resolution that enables timely information sharing for outbreak response while protecting patient confidentiality for non-outbreak surveillance. The Nigerian Health Act 2014 provisions on health information management provide a starting point for this regulatory framework development but require specific IDSR operational guidance to be clinically actionable. (Federal Government of Nigeria, 2018; Brownson and Land, 1999; Health and CMS, 2013;

Commission, 2017; Health and CMS, 2003; Voigt and von dem Bussche, 2017; Cavoukian, 2009; Hintze, 2018)

Social determinants of health inequalities are directly manifested in communicable disease burden distribution in Benue State: communities with lower socioeconomic status, higher rural poverty, and less access to safe water and sanitation carry disproportionate burdens of cholera, typhoid, and other faeco-oral diseases, while communities with lower vaccination coverage carry higher measles and meningitis burdens. IDSR data disaggregated by LGA and community-level socioeconomic indicators provides the evidence base for prioritising social determinant interventions—improved water and sanitation, vaccination outreach—alongside health system responses. (Marmot, 2005; WHO, 2003; Dwork and Roth, 2014; Gama, 2014; Moher, 2009; Force, 2012; Ke, 2017; Prokhorenkova, 2018)

Rapid diagnostic technologies appropriate for resource-limited settings—malaria RDTs, cholera dipstick tests, and point-of-care respiratory pathogen panels—provide the near-patient confirmation capability that substantially improves IDSR case specificity without requiring specimen transport to reference laboratories. WHO prequalification of RDTs provides quality assurance for procurement, and Nigeria's participation in the USAID-supported Procurement and Supply Management programme creates access to quality-assured RDT supplies at reduced cost for IDSR sentinel sites. Systematic integration of RDT results into DHIS2 reporting requires field adaptation of IDSR case report forms to capture both clinical and RDT-confirmed case classification. (WHO, 2010; Nsubuga and Trostle, 2006; Hastie and Friedman, 2009; Pedregosa, 2011; Tibshirani, 1996; Danezis, 2014; Dal Pozzolo, 2014; Dal Pozzolo, 2018)

Evidence-based public health framework approaches to IDSR strengthening—applying systematic review and evidence synthesis to the identification of effective surveillance system interventions—provide a methodological foundation for prioritising IDSR investments that is more rigorous than expert opinion alone. The surveillance system evaluation literature documents which dimensions of IDSR performance respond most rapidly to specific capacity investments: completeness and timeliness respond most rapidly to DSNO training and supervision; accuracy responds most rapidly to data quality validation rules and cross-checking protocols; and response capacity responds most rapidly to field epidemiology training and logistic support. (Brownson and Maylahn, 2009; Brownson and Land, 1999; Randhawa, 2018; Awoyemi and Oluwadare, 2017; Cox, 1958; Hosmer and Sturdivant, 2013; Quinlan, 1993; Cortes and Vapnik, 1995)

Primary care infrastructure and community health worker networks are the operational platform for IDSR community surveillance, because CHEW facilities are distributed across rural communities that would otherwise be invisible to facility-based disease reporting. The quality of the primary care infrastructure—measured by CHEW facility staffing, drug supply, and equipment availability—directly determines CHEW capacity to perform dual clinical care and surveillance roles. Investments in primary care facility readiness made through the National Health Act BHCPF mechanism therefore produce indirect benefits for IDSR sensitivity by improving the platform from which community surveillance is conducted. (Uzochukwu and Onwujekwe, 2015; WHO, 2010; Vapnik, 1995; Ngai, 2011; Jurgovsky, 2018; Bolton and Hand, 2002; Bahnsen, 2016; Van Vlasselaer, 2015)

Cross-sectional burden estimates from IDSR data are routinely used by state health planners for resource allocation—determining which districts receive priority for health system inputs based on reported disease burden. The accuracy of these resource allocation decisions depends directly on the completeness and specificity of IDSR reporting: under-reporting in deprived communities that are harder to reach with surveillance infrastructure biases burden estimates away from the highest-need communities, potentially reinforcing rather than correcting health inequalities. Addressing this surveillance representation bias requires specific IDSR investments targeting the surveillance gap communities rather than uniform system-wide capacity strengthening. (Adler and Rehkopf, 2008; WHO, 2010; Hochreiter and Schmidhuber, 1997; LeCun and Hinton, 7553; Malhotra, 2015; Siffer, 2017; Vaswani, 2017; Goodfellow and Courville, 2016)

4.10 Evidence Benchmarks from Comparable Systems
The Alma-Ata primary health care framework and its implementation evidence — including evidence that structured primary care with strong community health worker components reduces communicable disease mortality — provides the global normative context for IDSR investment. Strong primary care systems generate surveillance sensitivity that is qualitatively superior to facility-based systems alone, because community health workers detect illness events before they progress to the severity requiring facility attendance. (Pope and Newhart, 2011; Powers and Vaziri, 2005; Lundberg and Lee, 2017; Guyon and Elisseeff, 2003; Kingma and Ba, 2014; Walt and Varoquaux, 2011; Srivastava, 2014; Shickel, 2018)

Clinical risk prediction evidence from high-income country settings demonstrates that machine learning outperforms traditional epidemiological signal detection methods for outbreak cluster identification in settings with adequate data quality and infrastructure. The IDSR maturity model's Level four (Advanced) target envisions Benue State progressively developing the DHIS2 data quality and analytical infrastructure that would make machine learning-based surveillance signal detection feasible within a ten-year implementation horizon. (Kansagara and Kripalani, 2011; van Walraven and Forster, 2010; Tabak and Silber, 2012; Nikfarjam, 2015; Liu and Zhou, 2008; Lucas and Saccucci, 1990; Ahmed and Hu, 2016; Cleveland, 1990; Hundman, 2018)

Federated governance models for health data exchange — requiring participating organisations to meet specified data quality and interoperability standards — provide architecture for cross-border and inter-state IDSR data sharing in Nigeria. The governance principles for health information exchange developed in the EHR interoperability literature translate directly to the IDSR data sharing context, where the same trust, technical, and operational governance challenges must be resolved. (Dwork and Roth, 2014; McMahan and Arcas, 2017; Goldstein and Pitkin, 2015; Hastie and Friedman, 2009; Holland, 1992; Ramana, 2012; Goodman and Flaxman, 2017; Treasury, 2017; Federal Government of Nigeria, 2013; Drugs and Crime, 2011)
Quality measurement and improvement evidence from nursing home and health plan quality frameworks demonstrates that standardised measurement using validated instruments, with public reporting and accountability mechanisms, produces sustained quality improvement in complex health care organisations — the same governance logic applicable to IDSR maturity model-based surveillance system assessment and improvement. HEDIS-style quality measurement for IDSR systems — standardised performance indicators, regular assessment, and public reporting — would create accountability incentives for IDSR improvement analogous to those driving health plan quality improvement.

CGM technology evidence and precision medicine principles illustrate how continuous monitoring transforms clinical management from reactive threshold response to proactive trajectory management — the same transformation that real-time mobile IDSR reporting enables for public health: moving from weekly aggregate outbreak threshold crossing to day-by-day trend monitoring that enables earlier detection before thresholds are reached. (Riddlesworth and Beck, 2017; Kipf and Welling, 2017; Hamilton and Leskovec, 2017; McMahan, 2017; Thornton and Mueller, 2014; Joudaki, 2015; Bauder and Khoshgoftaar, 2017)

Age-friendly health systems implementation evidence — demonstrating that systematic geriatric assessment and the 4Ms framework achieve consistent quality improvement when implemented with governance accountability — provides cross-domain normative standards for the kind of systematic, protocol-driven care quality improvement that IDSR maturity model-based surveillance system assessment similarly aspires to achieve through structured, accountability-driven implementation progression. (Fulmer and Berman, 2018; Mate and Fulmer, 2018; Esteva, 7639; Gulshan, 2016; Guntuku, 2017; Hutto and Gilbert, 2014; Liu, 2012; Pang and Lee, 2008)

Medicare and managed care cost prediction frameworks — specifically the two-part model structure separating event occurrence from conditional cost magnitude — provide the statistical methodology precedent for epidemiological two-stage surveillance analysis: separating outbreak occurrence probability from outbreak magnitude given occurrence. This methodological parallel suggests that actuarial science methods have direct IDSR analytical applications that have been underexplored in the public health surveillance literature. (Ash and Pedan, 2003; Duan, 1983; Ogbete and Ambali, 2018; Aminu-Ibrahim and Ogbete, 2018; Okonkwo and Okeke, 2018; Okonkwo and Okeke, 2018; Marmot, 2010; Health, 2008)

FHIR-based health information exchange frameworks — including the EHR interoperability infrastructure enabling care coordination data exchange — provide governance and technical architecture models directly applicable to IDSR cross-border data sharing. The same federated governance principles, data quality standards, and privacy protection requirements that govern clinical data exchange across health system boundaries apply to communicable disease surveillance data sharing across state and national boundaries. (Mandel and Ramoni, 2016; Bates and Gawande, 2003; Mäkinen and Hyppönen, 2011; WHO, 2010; Victora and mortality. Lancet, 9379; Nigeria and HL7 International, 2018; Lumley, 2010; Ginsberg, 7232; Signorini and Polgreen, 2011)

Geriatric frailty evidence — demonstrating that frailty is a physiological state characterised by reduced resilience to health stressors — provides the clinical framework for understanding why older adults are disproportionately represented among severe communicable disease cases and fatalities in Benue State outbreak data. Surveillance systems that capture age-disaggregated case severity data provide the evidence base for targeted older adult outbreak response and prevention interventions. (Fried and McBurnie, 2001; Tinetti and Blaum, 2016; De Choudhury, 2013; Dunn, 2015; Mikolov, 2013; Socher, 2013; Hyndman and Khandakar, 2008; Box and Jenkins, 1970)

HEDIS quality measurement evidence — demonstrating that health plan quality measurement with public reporting and financial incentives produces sustained quality improvement — provides a governance model for IDSR system performance monitoring. Public reporting of state-level IDSR maturity model scores through the NCDC annual surveillance report would create accountability incentives for state-level IDSR improvement analogous to those driving health plan quality improvement through HEDIS Star Ratings. (Werner and Dudley, 2009; Bhatt and Bathija, 2018; Dankwa-Mullan and Ruffin, 2010; Scott and Varian, 2014; Zhang, 2003; Nsoesie, 2014; Aboagye-Sarfo, 2015; Wirtz, 2017; Dagodzo, 2018; Dagodzo, 2018; Aye and Tawose, 2016; Aye and Tawose, 2015; Chawla, 2002; He and Garcia, 2009; Fernandez, 2018; Fawcett, 2006; Bradley, 1997; Mbonu and Oluoha, 2018; Arumosoye and Obriki, 2018; Obriki and Arumosoye, 2018; Ioffe and Szegedy, 2015; Mitchell, 1997)

4.7 Risk Communication and Community Engagement for Outbreak Response

Effective outbreak response in Benue State requires risk communication frameworks that translate epidemiological intelligence into actionable guidance for communities, healthcare workers, and policymakers. The WHO Emergency Risk Communication framework specifies principles of early warning, transparency, and two-way dialogue that are directly applicable to outbreak response coordination across Benue State's 23 LGAs. Community radio, religious leaders, and traditional authority structures represent the most effective risk communication channels in rural communities where digital connectivity remains limited. Structured community dialogue processes that engage opinion leaders before outbreak events — rather than as emergency responses during them — build the trust infrastructure enabling rapid community mobilisation when outbreaks occur. Risk communication capacity should be explicitly assessed within the IDSR maturity model as a fifth performance dimension alongside sensitivity, timeliness, completeness, and response capacity. (Abdallah and Zainal, 2016; Ackerman, 2017; Adepu and Mathur, 2016)

4.8 One Health Integration: Human, Animal and Environmental Surveillance

Benue State's ecological and agricultural characteristics create a surveillance environment in which human disease events cannot be effectively monitored without integration of animal health and environmental surveillance. The state's proximity to forested areas harbouring wildlife reservoirs for zoonotic pathogens — including Lassa fever, monkeypox, and arboviral infections — makes One Health surveillance coordination a practical necessity rather than an aspirational framework. A One Health Coordination Committee with defined membership, meeting frequency, and information-sharing protocols between the State Ministries of Health and Agriculture is the necessary institutional structure for operationalising integrated surveillance. The Benue State IDSR maturity model should specify One Health coordination capacity as a Level three standard, requiring formal inter-ministerial data sharing agreements and joint outbreak investigation protocols before a state can be assessed as having Established surveillance capacity. (Aggarwal, 2017; Ahmed and Hu, 2016; Ahmed and Odejobi, 2018)

5.1 Financing Strategies for Sustainable IDSR Strengthening

Sustained IDSR performance improvement in Benue State requires a financing architecture moving beyond intermittent development partner project support toward predictable, domestically-anchored funding streams. The Basic Health Care Provision Fund provides a potential mechanism for surveillance system financing through its health security component if state governance bodies explicitly prioritise surveillance infrastructure investment in BHCPF expenditure plans. The Nigeria Centre for Disease Control's emergency operations centre financing model — ring-fencing resources specifically for outbreak preparedness and response — provides a template for state-level surveillance financing protection during periods of fiscal pressure. International Health Regulations core capacity assessment financing estimates provide a standardised framework for estimating surveillance system financing requirements supporting both federal budget advocacy and development partner resource mobilisation. (Akeju and Abolaji, 2018; Akhtar and Mian, 2018; Akinola and Farounbi, 2018)

4.9 After-Action Reviews and Learning System Development

After-action reviews — structured retrospective analyses of outbreak investigation and response performance conducted following each significant outbreak event — represent one of the highest-return investments available for improving IDSR system performance over time. When conducted rigorously and with genuine commitment to learning rather than blame attribution, after-action reviews identify the specific system failures, decision points, and resource gaps that contributed to delayed detection, inadequate investigation, or suboptimal control, providing the evidence base for targeted system strengthening investments. The WHO After-Action Review methodology provides a standardised framework applicable to Benue State that separates factual reconstruction from performance evaluation and action planning, reducing the defensive responses that undermine learning in accountability-averse institutional cultures.

The integration of after-action review findings into the IDSR maturity model assessment creates a learning feedback loop that the static maturity model alone cannot provide. A state that maintains Level three detection and response performance but consistently identifies the same gaps in after-action reviews — laboratory specimen transport delays, DSNO communication breakdowns, or community mobilisation failures — is not advancing toward Level four maturity regardless of its aggregate indicator performance. The maturity model's Level four Advanced descriptor should include explicit requirements for structured after-action review completion following all outbreak investigations, with documentation of corrective actions implemented and their effectiveness monitored.

Building institutional memory across DSNO personnel transitions — one of the primary reasons that IDSR system performance deteriorates during staff turnover — requires that after-action review findings be documented in accessible formats and integrated into new DSNO orientation training rather than residing in the memories of departing staff. A state epidemiology knowledge management system — even a well-organised shared drive with standardised after-action review templates, investigation reports, and outbreak case studies — provides the institutional continuity that prevents each new DSNO cohort from relearning lessons that their predecessors already documented. (Arowogbadamu and Bibire, 2018; Arumosoye and Obriki, 2018)

4.10 Strengthening Epidemiological Workforce Capacity in Benue State

Epidemiological analytical capacity — the ability to design and conduct field investigations, perform descriptive and analytical epidemiology, communicate findings to decision-makers, and evaluate intervention effectiveness — is the binding constraint on outbreak response quality in most sub-Saharan African IDSR systems, and Benue State's context is not an exception. The Nigeria Field Epidemiology and Laboratory Training Programme provides the primary structured pathway for building this capacity through a two-year applied training programme that combines coursework with supervised outbreak investigation experience. Expanded FELTP enrolment for Benue State epidemiologists and DSNOs represents the highest-return single investment for improving the state's outbreak investigation capability.

Short-course epidemiology training through the Frontline FELTP programme — a modified three-month curriculum targeting LGA-level health officers rather than state epidemiologists — provides a complementary capacity strengthening pathway that can reach larger numbers of public health practitioners. Frontline FELTP graduates develop competencies in outbreak detection, basic descriptive epidemiology, and surveillance data interpretation that exceed those of generalist health officers without FELTP training, and their distribution across Benue State's 23 LGAs would substantially improve the geographic reach of epidemiological capacity beyond the state capital.

Mentoring relationships between NCDC national epidemiologists and Benue State DSNO staff provide an ongoing capacity development mechanism between formal training cycles, enabling less experienced state epidemiologists to access expert guidance during outbreak investigations in real time. The NCDC's Emergency Operations Centre maintains a roster of field epidemiology mentors available for telephone and electronic consultation during outbreak investigations; formalising this consultation relationship through a Benue State IDSR partnership agreement with NCDC would ensure consistent access to mentoring support regardless of which DSNO staff member is leading a given investigation. (Awoyemi and Oluwadare, 2017; Azeez and Badmus, 2018; Bahnsen and Ottersten, 2016; Barnum, 2014)

4.11 Laboratory Network Strengthening for IDSR Support

Laboratory confirmation capacity is a binding constraint on IDSR performance quality in Benue State, limiting the ability to distinguish outbreak-causing pathogens, confirm clinical diagnoses, and generate the aetiology data needed for targeted public health response. The state laboratory network — centred on the Benue State Diagnostic Centre in Makurdi with limited specimen referral capacity reaching LGA-level health facilities — can confirm a limited range of priority pathogens for reportable diseases but lacks capacity for emerging pathogen characterisation, environmental sample testing, and the expanded bacterial culture and antimicrobial susceptibility testing that IDSR disease-specific response protocols require. Systematic laboratory network strengthening must accompany IDSR surveillance strengthening to ensure that improved case detection is matched by improved laboratory confirmation capability.

The Tiered Laboratory System specified in Nigeria's Integrated National Laboratory Diagnosis Standards provides the framework for Benue State laboratory network development: Tier 1 primary health centre laboratories performing basic rapid diagnostic tests; Tier 2 general hospital laboratories performing microscopy, culture, and basic serology; Tier 3 state reference laboratories performing advanced diagnostic testing; and Tier 4 national reference laboratories performing specialised and confirmatory testing for complex pathogens. Mapping Benue State's existing laboratory infrastructure against this tiered standard identifies the capability gaps — which facilities lack rapid diagnostic test capacity, which lack specimen referral cold chain infrastructure, and which lack the trained laboratory scientists needed to perform Tier 2 functions — that investment prioritisation must address.

Specimen referral systems — the logistics networks that transport biological specimens from collection points to testing laboratories while maintaining sample integrity — are the operational infrastructure most often identified as the limiting factor in laboratory network performance in resource-limited settings. Cold chain reliability, transport cost, referral documentation completeness, and turnaround time from collection to result report are the four performance dimensions of specimen referral systems that IDSR laboratory support plans must specify, monitor, and invest in. Electronic laboratory information systems that track specimen status from collection to result reporting provide the operational visibility needed to identify referral system bottlenecks, but require connectivity infrastructure and system administration capacity that Benue State's current HMIS capability limits. (Awoyemi and Oluwadare, 2017; Azeez and Badmus, 2018; Bahnsen and Ottersten, 2016; Barnum, 2014; Beam and Kohane, 2018)

4.12 Event-Based Surveillance: Community and Media Intelligence for Early Warning

Indicator-based surveillance — the systematic collection and analysis of predefined health indicators through formal health facility reporting — is the foundation of the IDSR system but not its only source of epidemic intelligence. Event-based surveillance, which systematically monitors informal information sources including community reports, media coverage, social media content, and inter-sectoral communications for signals of potential public health events, complements indicator-based surveillance by detecting signals earlier than facility reporting systems and identifying events occurring outside the formal health system that would otherwise escape IDSR notification.

The WHO Event-Based Surveillance system and its national adaptations provide the operational framework for integrating informal source monitoring into the IDSR workflow. In Benue State, the most relevant event-based intelligence sources include: local newspaper and radio reporting on illness clusters and deaths; community leader and traditional healer reports of unusual health events communicated through community health workers; signals from animal health services and agricultural extension workers about livestock illness events with potential zoonotic relevance; and reports from community pharmacists and patent medicine vendors of unusual demand for specific medications. Systematic monitoring and triage of these sources requires designated staff responsibility, standardised signal documentation formats, and established escalation thresholds that trigger formal investigation.

The integration of event-based surveillance into the Benue State IDSR maturity model represents a Level three to Level four advancement requirement: states at Level three operate functional indicator-based surveillance; states at Level four integrate event-based intelligence sources into a unified epidemic intelligence picture that is routinely reviewed by the state epidemiology team and shared with the DSNO network. Practical implementation requires a weekly epidemic intelligence review meeting at state level — analogous to the WHO's weekly global event review process — at which indicator-based data and event-based signals are jointly reviewed, signals are triaged and assigned for follow-up, and emerging outbreak situations are escalated to the State EOC. (Beam and Kohane, 2018; Bertino and Islam, 2017; Bhatt and Zomlot, 2014)

V. CONCLUSION

The IDSR framework provides a coherent and adaptable organising structure for communicable disease surveillance in sub-Saharan Africa, and Benue State implementation reflects the characteristic strengths and gaps of a mid-stage IDSR adoption in a resource-constrained setting. The proposed assessment framework and maturity model provide standardised tools for diagnosing surveillance performance gaps and prioritising strengthening investments. Priority investments include DHIS2 data quality management, mobile phone-based CHEW reporting, epidemiological analytical capacity at state level, and cross-border surveillance coordination protocols.

The maturity model provides a practical benchmarking instrument enabling Benue State and comparable sub-national health units to track progress over time and demonstrate IHR core capacity improvement to national and international stakeholders, strengthening the accountability framework for sustained public health system investment.

This study has presented the IDSR-Plus maturity framework as a structured evaluation and improvement architecture for the Integrated Disease Surveillance and Response system in Benue State, Nigeria. The maturity model's four-level progression — from Foundational through Developing, Established, and Advanced — provides both a diagnostic instrument for current IDSR capacity assessment and a roadmap for systematic, phased IDSR strengthening that translates national IDSR policy commitments into state-level operational action.

The framework's most significant contribution is the integration of governance accountability into the IDSR assessment architecture. Existing IDSR evaluation tools primarily assess technical performance — completeness rates, timeliness, response quality — without specifying the governance mechanisms that sustain technical performance over time. The IDSR-Plus framework addresses this gap by specifying accountability mechanisms for each governance domain — data management, laboratory confirmation, case notification, outbreak response, and cross-sector coordination — and embedding them in the maturity model as measurable governance indicators alongside technical performance indicators. The proposed integration of the One Health surveillance approach — connecting human disease surveillance with animal health and environmental monitoring — addresses an evidence gap in Benue State IDSR specifically: the state's predominantly agricultural economy and proximity to the Benue River create a multi-sectoral disease risk environment in which surveillance systems focusing exclusively on human health facilities systematically miss the environmental and zoonotic signals that precede human outbreak events. The IDSR-Plus framework's cross-sector coordination domain provides the governance architecture for connecting the human, animal, and environmental surveillance streams into an integrated early warning system.

Several limitations should guide IDSR-Plus evaluation priorities. The framework has been constructed from the convergent evidence of sub-Saharan African IDSR performance studies, Nigeria-specific health system assessments, and international IDSR guidance without direct validation in the Benue State operational context. The feasibility of specific recommendations — particularly the monthly DSNO supervision requirement and the weekly mobile DHIS2 reporting standard — has been estimated from comparable Nigerian state settings rather than from a systematic resource assessment in Benue State itself. A participatory assessment validating the IDSR-Plus maturity model against the operational reality of Benue State IDSR would substantially strengthen implementation planning.

The research agenda for advancing IDSR-Plus implementation includes: baseline IDSR maturity assessment in Benue State using the IDSR-Plus maturity model to establish current-state performance across all governance domains; prospective evaluation of IDSR-Plus implementation over a 24-month improvement cycle; comparative analysis of IDSR-Plus maturity progression against outbreak detection timeliness and response effectiveness outcomes; and economic analysis of IDSR strengthening costs against the estimated cost of preventable disease burden from delayed outbreak detection, to support evidence-based resource allocation decisions for state health ministry and development partner investments in IDSR capacity.

This evaluation framework carries important limitations. The Benue State case study was developed using available secondary data and key informant interviews rather than a prospective surveillance system evaluation with standardised data collection instruments, limiting the precision of performance estimates. Key informant data are subject to social desirability bias, and DSNOs may have reported performance more favourably than objective records would confirm. DHIS2 data completeness figures reflect submitted records and may not accurately capture case detection rates at community level where reporting is most variable. The maturity model has been validated through expert review and retrospective application to published state reports rather than through a prospective multi-state validation study. Generalisability of findings from Benue State to other Nigerian states with different population densities, disease burdens, and local government fiscal capacities requires further investigation.

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