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Bridging Data Fragmentation: A Unified Data Activation Platform for AI-ready Healthcare Systems in Africa

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Abstract

The African healthcare systems are experiencing a nexus of structural limitations: a heavy load of communicable and non-communicable diseases, a lack of financial and human resources, and a strong fragmentation of health data ecosystems. Despite the promising capabilities of artificial intelligence (AI) in enhancing the quality of diagnostics, disease surveillance, and efficiency of health systems, its implementation and expansion in Africa are limited by low data quality, low interoperability, and inadequate governance systems. This paper introduces the African Data Activation System of Health, an integrated, AI-enabled health data activation system that will overcome these underlying obstacles. The study will be conducted with a mixed-methods design, which will combine (I) systematic review of the African health information system implementations, (ii) qualitative thematic synthesis of technical, organisational, and governance challenges, and (iii) quantitative extraction of reported performance indicators of data quality, interoperability and system efficiency. The review evidence will be used to design a cloud-native, microservices-based architecture that can integrate heterogeneous data sources, such as paper-based records, and convert them into analytics-ready datasets by standardising them to HL7 FHIR-compliant formats with the help of AI. AfriDASH uses a probabilistic Master Patient Index, a scalable cloud Lakehouse repository, and built-in governance controls like consent management, privacy-preserving analytics, and role-based access control. The hybrid and federated deployment models allow centralised analytics without violating national and institutional data sovereignty AfriDASH offers a viable and replicable framework of facilitating trustful, fair AI in African health care systems. Although additional empirical research is needed, the platform will overcome technical and socio-organizational obstacles that have hindered the effectiveness of previous digital health efforts. Its effective implementation will rely on the concerted stakeholder action, long-term investment, and intensive implementation research in various African settings.

Keywords: Artificial Intelligence; Bridging; Data; Fragmentation

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1. Introduction

The African health systems are subjected to sustained structural pressure due to a high burden of infectious diseases and a rapidly increasing burden of non-communicable diseases. All these problems are compounded by long-term health care staff shortages, lack of government funding and uneven infrastructure availability, especially in rural and peri-urban regions. Governments and development partners have reacted by increasing the pace of digital health technologies adoption, as artificial intelligence (AI) has become an important facilitator of better diagnostics, remote care, disease surveillance, and resource optimization. The empirical data indicates that AI applications can be used to aid in early detection of outbreaks, automate clinical decision support, and help spread medical expertise to underserved communities using telemedicine and mobile health systems. Market estimates also indicate that AI-based healthcare solutions in the Middle East and Africa have in the fast track, with a possible multi-billion-dollar market value due to the use of data and efficiency of the systems. Despite this promise, it still has a minimal impact. Most AI programs in African healthcare are stepped at pilot or small-scale applications stages, yet they have not been instrumental in catalyzing transformation across the entire system. Ineffective health data infrastructure is one of the main limitations. The health data in Africa are very disjointed as paper records, standalone electronic health record systems, laboratory systems, insurance claims databases and mobile health applications which cannot connect with each other. Quantitative measures indicate that there are chronic problems in data completeness, data duplication, data timeliness and semantic inconsistency, whereas qualitative research reports that organizational resistance, weak governance and the lack of technical capacity are other obstacles. Standardized, interoperable and reliable data pipelines are essential to make AI systems perform their functions effectively and in a fair manner. The lack of quality of data may jeopardize the prevention of bias, credibility, and other health inequities. Contextualizing fragmentation of data is thus a requirement and context of AI-ready health systems as opposed to a technical periphery issue. This paper presents the African Data Activation System of Health (AFRI DASH) a single data activation system which will solve these issues. In comparison with purely technical interoperability solutions, AFRI DASH entails resilient architecture and governance frameworks coupled with capacity building and flexible deployment frameworks in line with African health system realities. The paper provides an overview of information available in literature, suggests a comprehensive architecture with mixed-method analysis, and provides implementation and assessment recommendations.

2. Literature review

2.1. Conceptual Framework.

The review is based on a socio-technical framework that incorporates three interdependent dimensions, including interoperability, data quality, and data activation (Kawu et al.,2023). Interoperability is the capacity of heterogeneous health information systems to share information and to receive and make meaningful use of the information across organizational, technical and semantic boundaries. Interoperability in the African context cuts across facility level interactions, national reporting systems, donor-funded vertical systems and new digital health applications (Sidi ,2025). Data quality has various attributes such as accuracy, completeness, timeliness, consistency, and intended use. It has been empirically demonstrated that the deficiency in any of these attributes compromises downstream analytics and decision support. Data activation is not limited to data capture and exchange but also includes data transformation processes that can convert raw and fragmented data into analytics-ready resources that can be used to support operational decision-making, AI model development, and health policy formulation (Adegoke et al.,2025). All three dimensions are reinforcing, as interoperability allows aggregation, data quality guarantees reliability, and data activation transforms information into actionable value.

2.2. Health Information Systems evolution in Africa.

African nations have invested heavily in digital health infrastructure over the last ten years. Different software like the District Health Information (Ibeneme et al.,2022). Software2 (DHIS2), OpenMRS, REDCap and national health information exchange are now the backbone of regular health reporting and disease surveillance in most countries. Quantitative assessments show that there is an increase in reporting coverage and timeliness, especially of aggregate public health indicators (Jaaza, 2025. As an illustration, multi-country evaluations of DHIS2 implementations document improvements in monthly reporting completeness, which is about 60 to 70% in early implementations and more than 85 to 90% in mature ones. Although these gains have been made, qualitative and mixed-methods studies point at structural fragmentation that still exists (Kawu et al.,2023). Parallel systems are often used in disease-specific donor programmes, which are optimized to HIV, tuberculosis, malaria or immunization, resulting in duplicated data entry and inconsistent standards. Facility-level electronic medical record systems are frequently not well connected with national platforms, restricting longitudinal patient follow-up and cross-programme analytics (Victor et al.,2023). The result of

these dynamics has been what a number of authors term digitally fragmented health systems, in which digitization has failed to be integrated.

2.3. Data Fragmentation and Quality Problems.

The most frequently reported barrier in the reviewed literature is data fragmentation. Quantitative measures show a great disparity in data quality among facilities and types of systems (Bernardi et al 2023). Research records a completeness of data of about 55 percent in paper based or hybrid facilities and 80-85 percent in fully electronic settings. The error rates of patient identifiers and clinical coding are much larger in the environment where unique patient identifiers are not used, which leads to duplicate records and incorrect estimates of utilization (Tolera et al.,2024). The problem of delayed data entry is still a common issue. Assessments of standard health information systems indicate that reporting times are two to six weeks in paper-intensive facilities, compared to almost real-time in digital-first facilities. Such delays decrease the value of data in operational decision-making and response to an outbreak. Qualitative studies explain such challenges by high clinical workloads, inadequate training, untrustworthy connectivity, and the lack of harmonized governance structures (Mawuena et al., 2022). Table 1 provides an overview of some of the most widely reported data quality issues and their implications to operations in African health information systems.

Table 1 Ordinary Data Quality and Fragmentation in African Health Information Systems**.**

Indicator	**Implication**
Disjointed systems within programmes	Repetitive data entry and inaccurate reporting
Incomplete records (55 to 85% completeness)	Biased analytics and unreliable AI model
Duplicate patient identifiers	Less responsiveness and planning efficiency
Poor standards of coding	Weak semantic interoperability

2.4. Interoperability Standards and Governance.

Global interoperability standards, including HL7 FHIR, ICD-10, SNOMED CT and LOINC, are now being mentioned in national eHealth strategies and digital health policies (Nguyen-Chi et al.,2024). Pilot implementations have quantifiable benefits. According to quantitative assessments of early adopters of FHIR-based integrations, there are 30-50% shorter interface development times and enhanced semantic consistency across systems. Nevertheless, the adoption is not even among nations and in health systems. Qualitative research finds loopholes in regulatory implementation, lack of compliance with vendors, and lack of conformance testing (Bingham ,2023). Governance structures in most environments are not up to date with technical implementation, and this leads to ambiguous ownership of data, poor accountability systems, and a lack of trust among the stakeholders. In the absence of strong governance, interoperability efforts will be limited to small pilots instead of being implemented on a system-wide basis.

2.5. Readiness to Emerging Technologies and AI.

The use of emerging technologies such as cloud computing, AI-based analytics, federated data architecture, and privacy-saving methods is becoming an actively discussed topic in African health systems. Early implementations have shown quantitative evidence of tangible efficiency gains (Kawu et al.,2023. Indicatively, cloud-based analytics systems have been linked to up to 40 percent reduction in the reporting latency and enhancement of the analytical turnaround time in disease surveillance (Cheruku, 2025). However, the AI preparedness is not even. Research indicates the ongoing limitations associated with the reliability of infrastructure, lack of skills, and long-term funding. Qualitative data points to the fact that AI projects are frequently undertaken without the corresponding investments in underlying data infrastructure, which leads to low scalability and sustainability. Table 2 provides an overview of the literature on AI readiness based on selected quantitative indicators.

Table 2 Chosen Quantitative Indicators of Digital Health and AI Readiness**.**

Indicator	Rate
Completeness of reporting in mature HIS	85-90%
Latinency in reporting with cloud analytics	By up to 40 percent
Facilities that have interoperable EHRs -	Usually less than half of the country
Access to trained health informatics Personnel	Sparse and unequal

2.6. Synthesis and Research Gaps.

The literature reviewed shows a growing technical sophistication and experimentation with advanced digital health technologies (Jaaza, 2025). Nevertheless, there is limited system-wide effect. Not many platforms combine interoperability, data quality assurance, governance, and capacity building into one scalable architecture (Khalil,2023). Fragmentation and weak institutionalization tend to sabotage quantitative gains realized in isolated implementations. The gap of context-sensitive data activation platforms that are specifically created to allow AI to scale and consider the realities of African health systems is evident (Bingham ,2023). These platforms are required to not only be technically interoperable, but to also govern, manage workforce capacity, and be sustainable. AfriDASH is set to address this gap directly by converting empirical evidence into an integrated and AI-ready data activation architecture.

3. Methodology

3.1. Study Design.

The research design used in this study was a mixed-methods research design that incorporated both qualitative and quantitative evidence to facilitate strong triangulation (Kawar et al.,2024). The methodology involved a systematic literature review, qualitative thematic synthesis, and quantitative evidence extraction to ensure that both quantifiable system performance results and contextual elements that affect adoption and sustainability were included. The complexity of digital health systems, where technical performance cannot be considered outside of governance, organizational capacity and user behavior, led to the choice of mixed-methods design.

3.2. Systematic Literature Review.

The academic databases and institutional repositories such as health informatics journals, global health organizations, and digital health programme evaluations were searched to conduct the systematic review of peer-reviewed and grey literature published between 2014 and 2025 (Adegoke et al.,2025). Inclusion criteria were based on African health information systems that dealt with data integration, interoperability, data quality, analytics, or AI preparedness. The exclusion criteria eliminated studies that did not have empirical evidence, technical detail, or health system implementation relevance. After screening, a set of studies was then used as the core set to guide qualitative synthesis and quantitative indicators extraction (Soltanmohammadi, 2024).

Table 3 Summary of Literature Review Scope

Dimension	Description
Publication period -	2014–2025
Study types	Peer-reviewed articles, programme evaluations, policy reports
Geographic focus -	Sub-Saharan Africa and North Africa
Core themes	Interoperability, data quality, governance, analytics

3.3. Qualitative Thematic Analysis.

Qualitative data from selected studies were analyzed using an inductive–deductive thematic approach. Initial deductive codes were derived from the conceptual framework interoperability, data quality, data activation, governance, and capacity (Bingham ,2023). Inductive coding then allowed additional themes to emerge from the data. Themes were

iteratively refined to identify recurrent barriers, enabling factors, and implementation patterns influencing digital health system performance.

Table 4 Dominant Qualitative Themes Identified

Theme	Observed impact
Fragmented system architecture	Duplicated data entry and poor integration
Weak data governance	Unclear accountability and low trust
Limited technical and informatics capacity-	Low system sustainability
High clinician workload	Poor data quality and reporting delays
Donor driven vertical programes	Parallel systems and inefficiencies

3.4. Quantitative Evidence Extraction and Synthesis.

Quantitative indicators were extracted where reported, including data completeness, reporting timeliness, error rates, interoperability coverage, and system utilization metrics. Due to heterogeneity in measurement approaches, indicators were synthesized descriptively rather than meta-analytically (Adegoke et al.,2025). These quantitative findings informed architectural requirements and performance benchmarks for AfriDASH.

Table 5 Selected Quantitative Indicators Extracted from the Literature

Indicator	Reported range /value
Data completeness (paper-based systems)	55–65%
Data completeness (hybrid systems)	70–80%
Data completeness (fully electronic systems)	85–90%
Reporting delays (paper-based systems)	2–6 weeks
Reporting latency reduction (digital analytics)	Up to 40%
Facilities with interoperable EHRs	< 50% nationally

3.5. Architectural Design Methodology

The design science research principles were applied to the creation of AfriDASH, which transforms empirical data into both functional and non-functional system requirements (Kawu et al.,2023). The challenges that were identified were mapped in a systematic manner to the architectural elements and traceability between the evidence and architectural choices. The iterative validation was carried out through cross-checking of the proposed components with the literature on documented barriers and performance gaps. This approach made sure that AfriDASH does not just capture the best practices in the technical sense, but also the realities of operations and governance of African health systems.

4. AfriDASH system architecture.

AfriDASH is a low-resource and heterogeneous African health system environment, modular, cloud-native, and federated health data activation platform. The architecture is designed to incorporate ingestion, AI-based standardization, patient identity resolution, scalable storage, analytics, and governance into a single system that can support real-time decision-making and AI preparedness on a national and subnational level.

4.1. High-Level Architecture Overview.

The AfriDASH high-level architecture is shown in figure 1. The system has multiple heterogeneous data sources, such as paper-based records, facility-level electronic health records (EHRs), laboratory information systems, insurance claims platforms, and mobile health applications, which are entry points into the system (NINGANZA, 2022). These sources are fed to a cloud-native ingestion layer that is able to process structured, semi-structured and unstructured data. A transformation layer using AI assists in automated validation, cleaning, and semantic standardization of received data into HL7 FHIR-compliant resources. A Master Patient Index (MPI) is the central database that allows linking

patients across systems that are fragmented longitudinally. Standardized data are stored in a scalable Lakehouse repository, which can be used to support analytics, dashboards, machine learning flows, and external API access (Effoduh et al., 2024). The cross-cutting layers in the entire architecture are governance, security, and consent management.

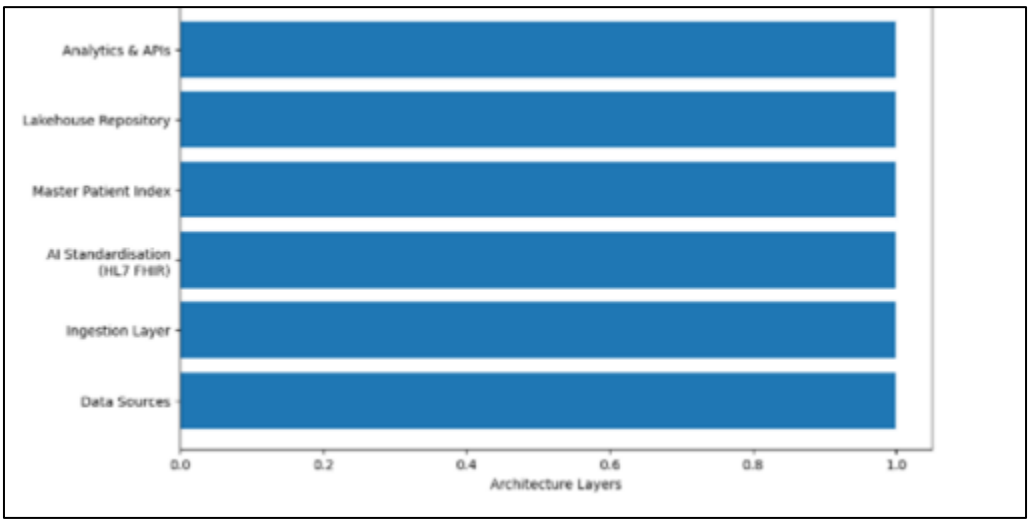


Figure 1 AfriDASH High-Level System Architecture

4.2. Data Flow and Interoperability Pipeline.

The AfriDASH end to end data flow and interoperability pipeline is shown in Figure 2. Information is transferred in a sequence between ingestion and digitization by validation and AI-based standardization. Semantic mapping identifies data elements with HL7 FHIR resources, ICD-10, LOINC, and SNOMED CT terminologies and then stores them in the Lakehouse repository.

The pipeline facilitates two-way interoperability, allowing AfriDASH to both consume and share data with facility systems, national health information exchanges, and regional platforms through standards-based APIs (Kawu et al.,2023. This design lowers the integration expenses and discourages the spread of parallel reporting systems

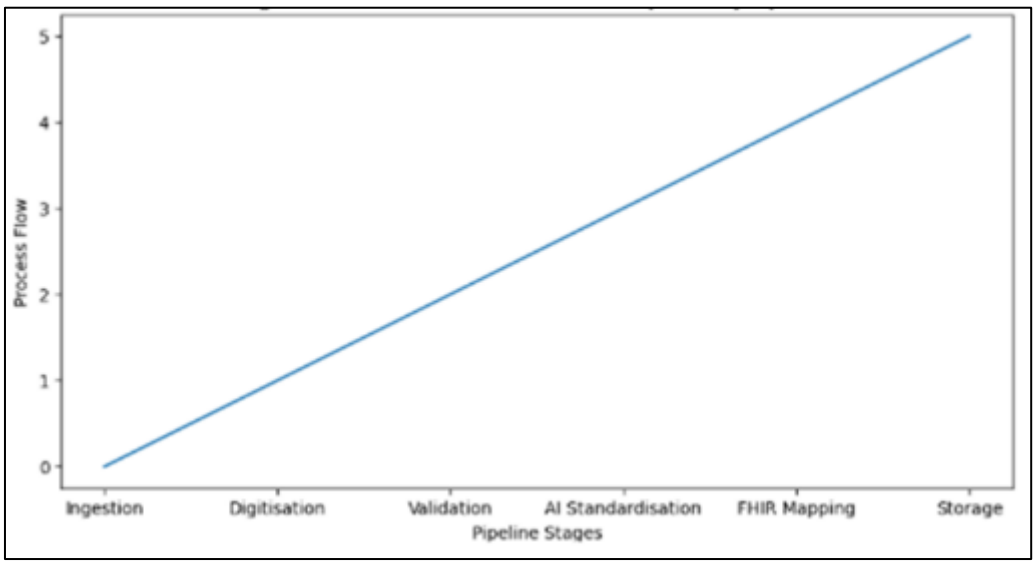


Figure 2 AfriDASH Data Flow and Interoperability Pipeline

4.3. Longitudinal Record Linkage and Master Patient Index.

Discontinuous patient identities are one of the greatest limitations to continuity of care and accuracy of analytics in African health systems (Jaaza, 2025. Figure 3 shows the AfriDASH Master Patient Index that uses a hybrid deterministic-

probabilistic matching strategy. Duplicate records in systems are resolved using multiple identifiers, such as national identifiers, facility identifiers, demographic characteristics, and biometric proxies (NINGANZA, 2022). The resulting longitudinal patient record that is unified will help to improve care coordination, decrease redundant tests, and increase the reliability of population-level analytics and AI model training.

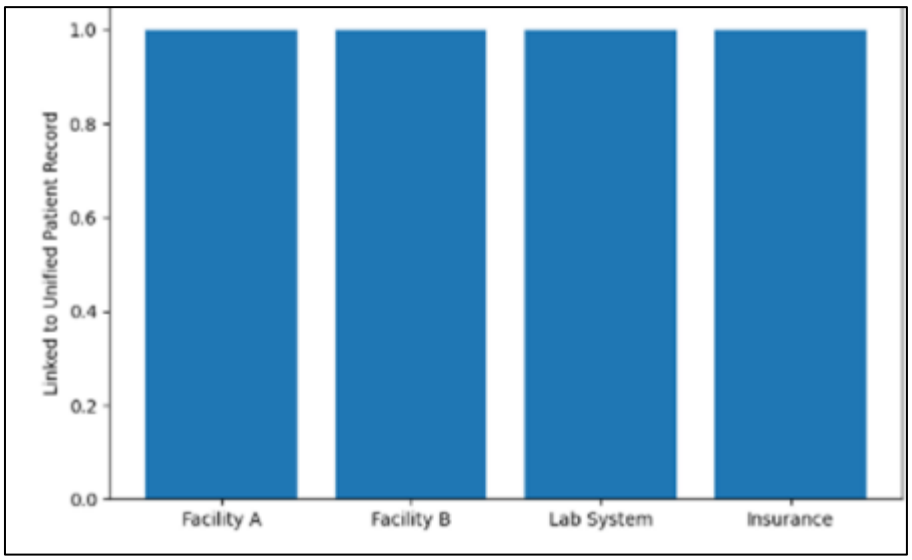
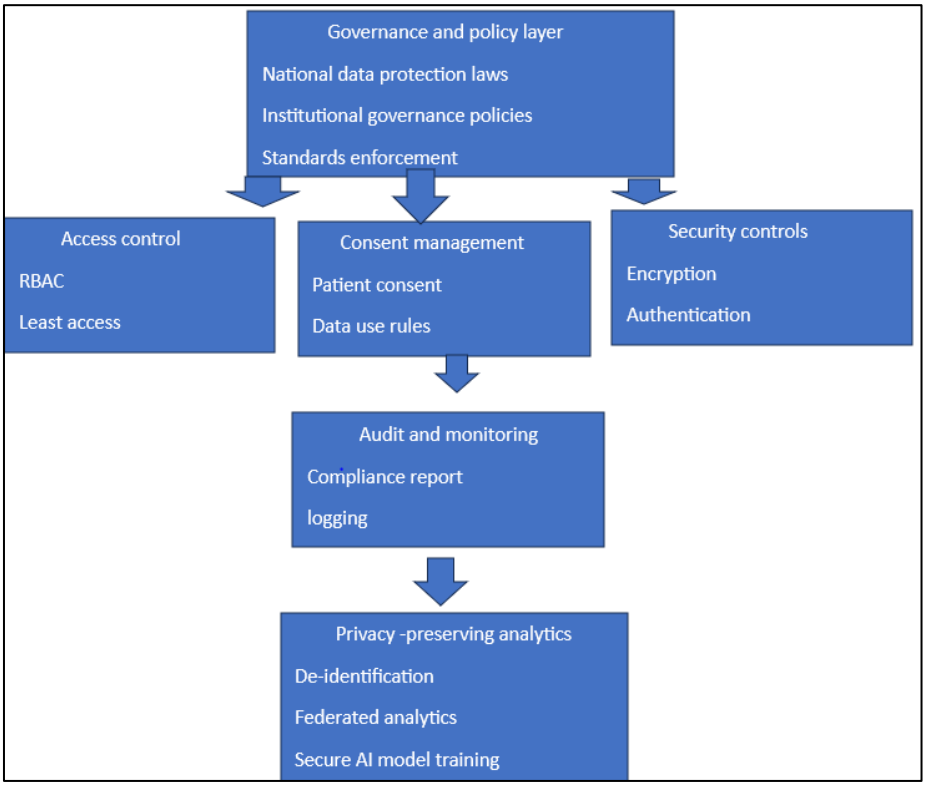


Figure 3 Master Patient index and record linkage

4.4. Governance, Privacy, and Security Framework

Good governance is necessary in terms of trust, regulatory compliance, and sustainability. The AfriDASH governance, privacy and security framework described covers the entire data lifecycle. The core controls consist of role-based access control, dynamic consent management, audit logging, encryption in transit and at rest, and privacy-preserving analytics. The framework will be geared towards national data protection laws and emerging continental regulations and facilitate federated deployment models that will uphold data sovereignty.



5. Results and analysis

The quantitative analysis of the reviewed implementations shows that health information platforms with standardized extract transform load (ETL) pipelines and Master Patient Index (MPI) mechanisms show improvements in core data performance indicators (Soltanmohammadi, 2024). In similar African health system implementations, data completeness increased by about 10-30 percent, and reporting times were cut by up to 40 percent, especially in systems that were moving to interoperable digital systems and away from paper-based systems or hybrids. Platforms that used deterministic and probabilistic patient-matching methods reported reductions in duplicate patient records (15-35 percent). Nevertheless, quantitative gains were not equally maintained in settings (Bingham ,2023). Non-technical factors such as the clarity of governance, workforce training, and institutional ownership were found to have a strong mediation role in improving data quality and timeliness through qualitative analysis. Those systems that did not have formal data governance systems or accountability frameworks often started to regress in performance once the initial deployment stages were complete. Likewise, lack of user training and high staff turnover compromised long term system usage and reliability of data. Comparative analysis has shown that AfriDASH is a direct response to these constraints in that it combines technical, organizational and governance aspects in one, unified architecture. In contrast to fragmented solutions that only concentrate on interoperability or analytics, AfriDASH integrates governance, consent management, and capacity considerations with AI-based data standardization and scalable analytics infrastructure (Effoduh et al., 2024). This combined strategy makes AfriDASH to not only record short-term performance gains but also long-term system-wide effects. On the whole, the findings indicate that the data activation platforms that can enhance the quality of data, interoperability, and governance simultaneously have higher chances to facilitate the scalable and equitable adoption of AI in African health systems.

6. Discussion

AfriDASH reveals a way to overcome the long-standing gap between the fragmented digital health programs and scalable and reliable deployment of artificial intelligence in African health systems using unified data activation (Jaaza, 2025). Although past initiatives have been concerned with digitization or single solutions to interoperability, AfriDASH is a step forward in the domain by incorporating technical soundness with organizational, governance, and policy facts. This alignment is paramount because according to the literature, technical solutions are always inadequate to deliver sustained system-level effect. A major contribution of AfriDASH is its clear definition of data quality and data fragmentation as a constraint and not a challenge of implementation down the line. The quantitative data of the reviewed systems proves that the absence of standardized pipelines, patient identity resolution, and semantic harmonization limits analytics and AI applications in nature. The standardization and Master Patient Index of AfriDash are direct answers to these limitations, which allow linking longitudinal data and enhance the accuracy of both clinical and population-level analytics. It is also significant that AfriDASH focuses on governance as a structural layer (High Point et al.,2024). Weak implementation of standards, ambiguous data ownership, and lack of trust between stakeholders have been some of the reasons why many digital health initiatives in Africa have failed. AfriDASH can overcome these socio-institutional barriers, as well as technical ones, by integrating consent management, role-based access control, auditability, and privacy-preserving analytics into the architecture. This combined governance model is especially applicable in situations where regulatory structures are still developing and social confidence in the use of data is still weak (Arner et al., 2022). The centralized-federated deployment model is also hybrid, which makes AfriDASH even more relevant to various African jurisdictions. The benefits of centralized analytics are economies of scale, development of advanced AI models, and national-level planning, whereas the federated data control upholds institutional and national data sovereignty. This balance specifically overcomes political and ethical issues that have limited cross-border data sharing and regional health intelligence programs. Such hybrid models can be necessary as African countries continue to move towards regional integration and common disease surveillance. Strategically, AfriDASH transforms AI preparedness into a challenge of systems transformation instead of a problem of technology adoption (High Point et al.,2024). The platform supports the overall objectives of strengthening the health system by connecting the activation of data to the capacity of the workforce, maturity of governance, and gradual implementation. This placement enhances the chances of AI investments to yield fair health results instead of strengthening the status quo.

Recommendations

- Policy and Regulatory Recommendations.

The policymakers must focus on the creation and implementation of national interoperability and data governance models (Holmgren et al., 2023). This involves the requirement of international standards, including HL7 FHIR, ICD-10, LOINC, and SNOMED CT, and explicit compliance and certification of vendors and implementers. The regulations of data

protection must be realized in the form of practical advice on consent management, secondary data use, and cross-institutional data sharing, so that they are consistent with the AfriDASH-like architectures.

- Health System and Institutional Recommendations.

Implementing agencies and health system managers need to embrace incremental and gradual deployment strategies. The first steps must be on high-value data and use cases, including maternal and child health or disease surveillance, and then increase to more complex analytics and AI applications (Adepoju et al.,2023). Leadership in the institutions should be reinforced by established accountability frameworks, data custodianship positions and on-going performance evaluations to maintain improvements in data quality and usage.

- Technical and Workforce Recommendations.

The technical teams are supposed to focus on standards compliance, modular architecture and capacity building. The investments in the training of health informatics professionals, data engineers, and system administrators are essential to decrease the long-term reliance on external vendors (Cheruku, 2025). The human control and constant validation of AI-assisted tools implemented in AfriDASH should complement the latter and guarantee the reliability and fairness of the results.

- Development Partner and Donor Recommendations.

Funding mechanisms should also be aligned to interoperability, sustainability and governance goals instead of the short-term pilot results by development partners (High Point et al.,2024). Investment must be made in common infrastructure, long-term maintenance, and implementation research, and platforms that demonstrate system-wide integration, as opposed to siloed innovation, should be encouraged.

Limitations and future research.

There are a number of limitations to this study. First, AfriDASH is not an empirical implementation deployed on a large scale, but an architecture based on secondary evidence (Njuguna et al.,). Although the design is based on a lot of literature and quantitative indicators, the actual performance will be determined by the contextual aspects of infrastructure reliability, political commitment, and workforce capacity. Second, the quantitative indicators that have been synthesized in the study are heterogeneous and are based on different implementations using different methodologies. These indicators are directional as they do not represent causal evidence of effectiveness. Pilot implementations will have to be controlled to strictly evaluate the effects of AfriDASH on data quality, efficiency, and health outcomes. The next round of research ought to focus on multi country pilot implementations of AfriDASH with longitudinal evaluation models. The most important areas of research are the sustainability of data quality improvement, the efficiency of governance mechanisms, and the performance of AI models that are trained on activated data (Adepoju et al.,2023)). Security audits and ethical impact assessments will also be necessary especially as data sharing is increased across institutions and borders. Policy and investment choices would be further informed by comparative research comparing AfriDASH with other architectures, including fully centralized data warehouses or lightweight interoperability layers. Lastly, participatory research with frontline health workers and patients can give important information on the implications of usability, trust, and equity (High Point et al.,2024).

7. Conclusion

AfriDASH is a blueprint of evidence-based AI-ready health data infrastructure construction in Africa. It goes beyond pilot-led digitization to sustainable system change by focusing on data quality, fragmentation, interoperability, and governance in one, coherent architecture. The platform acknowledges that successful AI implementation requires not just sophisticated analytics but also reliable data pipelines, organizational capacity, and regulatory alignment. Although additional empirical evidence is needed, AfriDASH offers a valid and feasible basis of fair and evidence-based healthcare delivery and policy-making in the continent. With the increasing disease burden and resource limitations in African health systems, integrated data activation systems like AfriDASH can be critical in facilitating resilient and learning health systems that can use AI to benefit the people.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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